1-1-2013

Modeling Multiple Occupant Behaviors in Buildings for increased Simulation Accuracy: An Agent-Based Modeling Approach

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Abstract
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Degree Type
Dissertation

Degree Name
Doctor of Philosophy (PhD)

Graduate Group
Architecture

First Advisor
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Second Advisor
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Keywords
agent-based modeling, building simulation, building technology, energy efficiency, human behavior, simulation coupling

Subject Categories
Architectural Engineering | Architecture | Social and Behavioral Sciences

MODELING MULTIPLE OCCUPANT BEHAVIORS IN BUILDINGS FOR INCREASED SIMULATION ACCURACY: AN AGENT-BASED MODELING APPROACH

Yoon Soo Lee

A DISSERTATION

in

Architecture

Presented to the Faculties of the University of Pennsylvania

in

Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

2013

Supervisor of Dissertation

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MODELING MULTIPLE OCCUPANT BEHAVIORS IN BUILDINGS FOR INCREASED

SIMULATION ACCURACY: AN AGENT-BASED MODELING APPROACH

Dedication

To my loving family

for their unconditional support

and

tolerance throughout this

LONG

journey.

ABSTRACT

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Yoon Soo Lee

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The dissertation addresses the limitation of current building energy simulation programs in accounting for occupant behaviors, which have been identified as having significant impact on the overall building energy performance. It introduces a new simulation methodology using an agent-based modeling approach that helps to both predict real-world occupant behaviors observed in an operating building and to calculate behavior impact on energy use and occupant comfort. A series of experiments has been conducted using the new methodology and yielded simulation results that not only distinguish themselves from current simulation practices, but also uncover emerging phenomena that enhance the insights on building dynamics.

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1. INTRODUCTION

The section is composed of two parts that serve as a preamble to the human behavior research covered in the dissertation. First, the emergence of human behavior in architecture is discussed, which is mainly a theoretical backdrop that underscores the relationship between human behavior and building performance. Secondly, different methodological approaches are summarized to augment the effort to deal with the uncertainties of human behavior.

1.1. Emergence of Human Behavior in Architecture

The building occupant is an essential component in our built environment, and its prominence in building research has recently started to gain recognition. The studies on comfort and adaptive control [Brager et al., 1998], lighting control [Bourgeois et al., 2006; Lindelöf et al., 2006], operable window control [Rijal et al, 2007], and shading control [Reinhart, 2004] are some of the few research topics that began to investigate the occupant behavior and/or behavioral influences in building operation. However, there are few instances where this sensitivity towards occupant behavior plays a definitive role in the decision making process.

At the onset of building design process, occupant behaviors like occupancy and operation schedules play an important role in formulating design decisions. Behaviors are also relevant to building performance throughout the life of building operations. For example, occupant behaviors can cause the wear and tear of building infrastructure and can influence the microclimate of individual spaces, which are all closely connected to the overall energy performance of the building. The objective of the dissertation is to uncover salient occupant behaviors in buildings, along with their implications for energy performance or efficiency, and thus underscore the emergence of occupant behavior and its increasing role in shaping building research and practices. This objective is supported by three discussions related to the significance of occupant behaviors in architecture: First, the importance of the occupants' role in the pursuit of energy conservation is explained, which is a departure from the commonly aimed efforts for system-oriented optimization for energy efficiency. Then, the relationship between occupant behavior and energy performance is elaborated on.

1.1.1. Role of Human Behavior in Energy Conservation

Energy conservation, as commonly understood among energy policymakers, is defined as reduced energy consumption through lower quality of energy inputs, for example, enforcing speed limits for cars [Herring, 2006]. In the building sector, the current approaches to energy conservation mainly focuses on achieving its goals by systems-oriented optimization. However, this dissertation addresses energy conservation from a different angle by emphasizing human-oriented viewpoints, based on the criticism of accounting for conservation factors that neglect the actual energy use of the occupants [Patterson, 1996]. This is because maintaining the quality of energy input to the end users seems to play an important role in the overall energy efficiency of buildings. For instance, a lower-quality energy input, such as insufficient cooling/heating in a space, will increase occupant dissatisfaction in thermal comfort, and thus incur increased control over his/her thermal environment. An example of such a control is operating a space heater or personal fan, which will not only help to regain the level of occupant comfort, but also create added energy uses. This behavior, through user manipulation of the built environment, is a typical form of a rebound effect that is antithetical to building energy conservation regardless of the high efficiency achieved by the mechanical systems [Zimmermann, 2006]. This also reduces the ability to make sound predictions of building energy demand early on in the design phase, which is critical in making design decisions that pertain to energy conservation.

Hence, the objective of this dissertation is to investigate energy conservation at the end-user level (which will be referred to as energy efficiency) in tandem with efficacy at the systems level. The pursuit is grounded on Ackoff's concept of systems thinking where a system is a functioning whole that cannot be divided into independent parts [Ackoff, 1996]. Therefore, a building can be viewed as a dynamic and functional whole, made up of subsystems that form a hierarchy in the following sense: *animated systems (human beings)* that closely interact with *deterministic systems (mechanisms),* and are then influenced by *social systems*, which are all contained in *ecological systems* [Ackoff, 1996]. And the success of the system is to make sure that the subsystems are integrated to create synergy towards achieving a common goal [Rush, 1986]. For this study, the goal is to predict energy consumption in buildings by taking occupant behaviors into consideration.

1.1.2. Human Behavior and Impact on Building Energy Use

In response to the thermal monotony in most mechanically conditioned buildings, various scientific studies claim that occupants are more satisfied with a diversity of thermal conditions, or they feel the need to respond to the changing environmental stimuli [Heschong, 1979][Baker et al., 2000]. The notion of acclimatization is not a new phenomenon; both ancient dwellers in Mesa Verde caves and in Persian Plateau courtyard houses migrated within the indoor space to adapt to the changing diurnal and seasonal climatic conditions [Merghani, 2004]. This is also the principle behind the adaptive comfort model, which emphasizes the occupants' increased tolerance to the immediate environment through thermal adaptation [Brager et al., 1998]. Among building occupants, acclimatization can also be manifested as the active control of their surrounding thermal environment in order to increase the level of comfort in the workspace (similar to the previous example of occupants using space heaters or personal fans). The behaviors associated with these actions of active control are of primary interest, because they not only define the microclimate of individual's space but also affect the way energy is used in the building. A handful of previous studies attests to this correlation between occupant behavior and building energy performance [Hoes et al., 2009][Baker et al., 2000] [Dusée, 2004], which will be elaborated upon later on in the dissertation.

On one hand, a better understanding of occupant behavior will help foment an improved energy prediction model – a direct causality that would contribute to better systems design and control algorithms. From a different perspective, one could also predict energy inefficiencies due to occupant behavior, allowing architects and engineers to better articulate occupant control at an early stage in the design process [Steemers et al., 2004].

1.2. Uncertainties of Human Behavior

Human behaviors are mostly choices made that are inherently haphazard and transient. Simon has categorized the uncertainties of human behavior as being the 'phenomena and events in any environment where they are considered to be random because we simply have no better way of characterizing them' [Simon, 1996]. The effort in trying to better understand human behaviors and behavioral uncertainties – particularly in the context of the built environment – has yet to gain a deserving recognition in the building science community. In other disciplines, behavioral prediction models can be conceived through literal observation, assuming that the behavior of interest is clearly defined [Fishbien et al., 2010]. Fortunately, a handful of recent studies has shown promising advancements in uncertainty estimation using the capabilities of computer simulation [Simon, 1996][Malkawi et al., 2004]. The goal of this dissertation is to reflect these theoretical and methodological frameworks onto human behavior prediction and/or modeling in buildings.

In response to the complexity of human behavior (or any behavioral uncertainty) prediction, Simon insists on methods of abstraction and simplification without a detailed scrutiny of inner environment, as behavioral identity resembles only few properties of the whole [Simon, 1996]. This is analogous to how a mathematical theory is reduced to a simple equation, which is less of a representation of the inner environment and its interconnectivity, but more of the phenomenon of interest. Such abstraction and simplification is also justified in Poincare's discussion, where he characterizes the *reasoning by recurrence* in a single formula that contains an infinite number of syllogisms [Poincare, 1952]. German philosopher Schlick also assures us that by means of simplicity, scientists succeed in representing a series of observations through a simple formula or several regularities [Popper, 1959]. For a specific methodology for abstraction, the use of the probability distribution (mostly stochastic process) is widely used for uncertainty analysis, such as in human behavior (and social science in general) predictions [Simon, 1996][Sokolowski, 2009].

Although abstraction and simplification can become vague and relative, the use of statistics seems to be justified for the decision-making process in various territories. The real challenge is actually identifying the phenomena of interest and the attributes (variables) that trigger them, i.e., knowing ‘what’ to predict and ‘what’ evokes them. This process can sometimes be ad hoc, increasing the tension by contributing to the uncertainty all the more. As a feasible direction, this dissertation will adopt the spirit of the social-constructivist approach, which argues that scientific knowledge should integrate both social and natural phenomena [Bijker et al., 1987]. This is because behavioral intentions in buildings are not manifested in a single causal relationship, but are instead intricately interweaved with multiple causalities – factors that stem from the physical, cultural, psychological, social, and so on. In line with ideas of social constructivism, H.M. Collins suggested a research methodology, such as use of questionnaires and other techniques for gathering ‘information’ about societies, that is based on the assumption that ‘useful knowledge’ can be attained not just by studying the behavior itself, but also the environment in which it takes place and the rules of thumb for solving complex problems (defined as *expert system* or *intelligent knowledge-based systems*; it is one of the promising routes for artificial intelligence research) [Bijker et al., 1987].

The Background section of the dissertation provides a summary of the literature that underscores the importance of human factors in building research, associated limitations, and a potential methodological approach that could be advantageous to studying behaviors.

The Methodology section presents an in-depth overview of the theoretical and technical framework used in the dissertation to study occupant behavior in buildings. This includes various methods to measure and quantify human behaviors, to predict future behaviors, and to simulate the behavior impact on building energy consumption and occupant comfort.

The Experiments section presents a sequence of simulation experiments that test the ideas and methods discussed in the dissertation. The experiments uncover how behavior related information is interpreted in current simulation programs. They also address fundamental limitations of current simulation programs that lack in accounting for realistic occupant behaviors. For the most part, the section demonstrates the application of the new methodology proposed in the dissertation, or the new simulation approach to incorporate the impact of occupant behaviors, and draws findings about building dynamics incurred from human factors.

The Conclusion section includes the lessons learned, limitations and contributions of the dissertation, and future research goals.

2. BACKGROUND

The overarching theme for the dissertation is about achieving building energy efficiency and saving energy. Among the different strategies for constructing efficient buildings, the dissertation focuses on one that is related to accurately predicting the building load so that energy-saving features can be implemented accordingly – e.g., optimally sized mechanical systems, shading devices, ventilation strategy, façade design, etc. The effort in increasing the prediction accuracy of building load is analogous to increasing the accuracy of building energy simulation (henceforth, building simulation) capabilities. In line with the discussion of human behavior, the objective of the dissertation will try to find the relationship between building occupant behaviors and building simulation accuracy. In other words, it will tackle the limitations of building simulation by way of better incorporating occupant behavior feedback into the simulation process. A commonly identified limitation is the discrepancy between simulated and actual building energy consumption data, which is typically greater than 30 percent [Yudelson, 2010]. In an effort to increase the prediction capabilities of current building simulation programs, the dissertation will focus on the impact of occupant behavior and behavioral feedback on bridging the gap between the simulated and actual energy consumption (Figure 2.1).

The importance of occupant behavior in buildings has long been studied in the discipline, and is commonly cited as having a prominent effect on the whole-building energy consumption. Hence, the dissertation assumes that accurately accounting for behavioral impact into building simulation will also increase the accuracy of the simulation itself. In this section, previous research efforts that underscore the impact of occupant behavior in buildings (and the shortcomings of those that neglect to do so) will be discussed. In addition, developments in building simulation in the past decade are introduced, with an emphasis on how uncertainties like human behavior can be simulated.

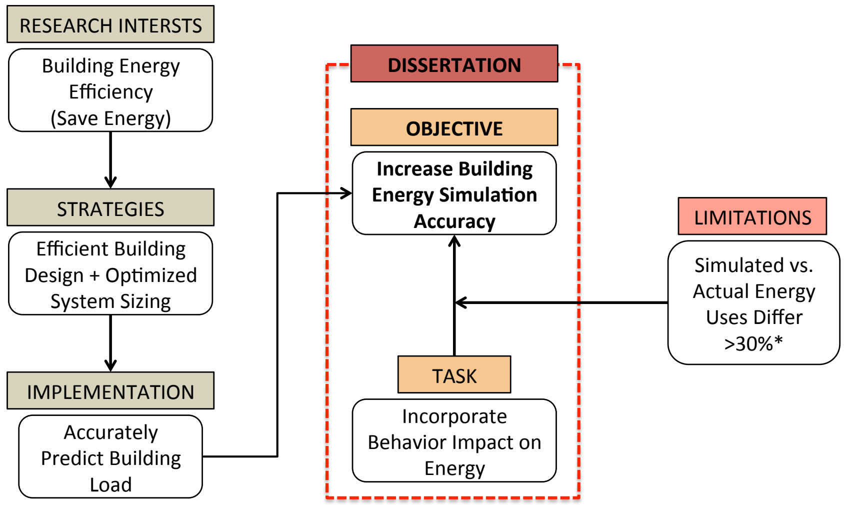


Figure 2.1 Research interest and objective

2.1. Literature Review

The problem statement of the dissertation is to find the theoretical framework to measure and quantify building occupant behaviors and a methodology to translate behavioral information into a performance (mostly energy) metric. But fundamentally, the question whether increased simulation accuracy can, indeed, be achieved by accounting for occupant behaviors in current simulation practices. As a justification for pursuing human behavior research, the following summarizes the shortcomings of current building simulation programs.

Masos and Grobler point out that occupant behavior is the weakest link in the energy efficiency and conservation equation, and through case studies illustrate that accounting for behavioral changes could have higher energy saving potentials compared to those achieved from technological solutions [Masoso et al., 2010]. As a consensus, many other researchers in the discipline have emphasized the importance of accurately conducting human/behavioral feedback, as it is reflected as increased prediction accuracy for simulation programs as a whole [Newsham, 1994][Bourgeois et al., 2006][Mahdavi, 2001].

Then, what is the reason for this oversight? The following excerpts explain how the simulation process became independent of the human and behavioral aspects.

Degelman insists that building simulations provide an accurate prediction only when building user influence is minimized or not possible at all [Degelman, 1999]. Moreover, results obtained from simulation programs are typically validated with measured data. So in order to satisfy a short-term energy prediction, for example, avoiding the hassle of dealing with the uncertainties of human/behavioral feedback has been justified [Zimmermann, 2006].

Human activities and consequent behavioral patterns are inherently dynamic in characteristics. In the past, the notion of the dynamics in the simulation world was somewhat received as the availability of a more flexible, open model, which integrates algorithms developed by different groups [Lewis et al., 1990].

While the notion of incorporating human/behavioral feedback resonates with the capabilities to adapt to the dynamic uncertainties of the built environment, such as the contextual conditions like weather and light level, as well as occupant intervention and building control operations [Mahdavi, 2001], the feedback mechanisms in current simulation programs are limited to those that are based on short-term instances that greatly lack the responsiveness to such dynamic conditions. This is mainly due the fact that most prediction models are set up in advance, using historical data that are hardly changed after implementation [Yang et al., 2005]. In fact, most prediction models are still not sufficient enough to produce an accurate forecast for complex, non-linear correlations, such as rapid weather changes, let alone human behavioral patterns [Khotanzad et al., 1995]. And occupants are treated as merely a fixed metabolic heat generator passively experiencing the indoor environment [Newsham, 1994].

Some of the major challenges identified in the literature also indicate that it is extremely difficult to develop a mathematical formalism of human behavior, and hence, the cost and effort to build good models can be very high [Hensen, 2002][Fernlund et al., 2002], leading to an oversimplified representation of human behaviors [Pan et al., 2006]. Nevertheless, the fundamental limitations are a lack of solution process and overwhelming computational data storage requirements [Somarathne et al., 2005]. Hence, a need for back-tracking algorithms that analyze the past behavior and calibrate the simulation programs for improved predictions has emerged [Mahdavi, 2001][Andreassi et al, 2009].

The literature has consistently pointed out the absence of human/behavioral feedback in simulation programs as a significant issue. However, a greater urgency inheres in the fact that the importance of human/behavioral feedback has been underrated in current building research. Therefore, the following excerpts that discuss the impact of occupants and behaviors on building performance will justify the path that the dissertation is taking – a path towards capturing the human/behavioral feedback and its implications on building energy performance.

User behavior is one of the most important input parameters influencing the results of building performance simulations. Perhaps it has a much larger influence on the energy performance of a building than the thermal process within the building façade [Hoes et al., 2009]. In particular, human/behavioral influence seems to be a prerequisite for passive control systems, and also is important in decision-making for fully sealed, mechanically controlled buildings [Hoes et al., 2009][Degelman, 1999].

The application of user behavior models with higher resolution and higher complexity will improve the understanding of the relationship between building, user and building performance [Rijal et al., 2007]. A real-time occupant feedback system can fill the missing void in the current simulation cycle, and ultimately resolve the uncertainties of occupant behavior while increasing prediction accuracy [Malkawi, 2004].

In a study about energy saving behaviors, the attitude of office employees had a positive effect on energy use, while office occupation level had a negative effect [Dusée, 2004]. In fact, occupants can change the energy use of similar buildings by a factor of 2 [Baker et al., 2000].

The references from existing literature help to set the scope of the dissertation – a research with a goal of investigating the way to connect the feedback from occupant behaviors to the building simulation programs in order to accurately predict a building's energy load. The effort will help to increase the simulation accuracy, and ultimately will help to envision design strategies for improved energy efficiency.

2.2. Evolution of Computational Building Simulation

2.2.1. Social Science Modeling

Simulation technology is a construct of multiple disciplines, such as physics, mathematics, computer science, and so on. Simulating human behavior in buildings, in particular, can make good use of the knowledge in social science modeling. Social science modeling can be categorized into three modeling typologies [Sokolowski et al., 2009]:

- Statistical modeling: a traditional method for the discovery and interpretation of patterns in large numbers of events.
- Formal modeling: a method that provides a rigorous analytic specification of the choices actors can make and how those choices interact to produce outcomes.
- Agent-based modeling: a method allowing for the observation of aggregate behaviors that emerge from the interactions of large numbers of autonomous actors.

In the dissertation, the decision-making process for occupant behaviors will be determined by agent-based modeling; by modeling agents individually, agent-based modeling accounts for the effects of the diversity among agents in their attributes and behaviors in the pursuit of understanding those of the whole system [Macal et al., 2010].

An agent can be defined as a system that acts and thinks like a human, which ‘operates under autonomous control, perceive its environment, adapts to changes, and is capable of taking on specific goals’ [Russell et al., 2003]. This autonomous control is perhaps the most important characteristics of an agent, which can simply be a reactive ‘if-then’ rule, a complex behavior modeled by adaptive artificial intelligence technique, or an ability to learn and change its behaviors in response to its experiences [Macal et al., 2010]. Other essential agent characteristics are summarized as follows [Macal et al., 2010]:

- Agent is a self-contained, modular (i.e., it has boundaries), and uniquely identifiable individual.
- Agent has a state that varies over time.
- Agent dynamically interacts with each other that influence its behavior.
- Agent may be adaptive by having rule of more abstract mechanisms that modify its behaviors.
- Agent may be goal-directed.
- Agent may be heterogeneous to consider the full range of agent diversity.

Agent-based modeling is a simulation approach that consists of these agents, which are governed by rules of behaviors or a certain human-like (rational) process, e.g., instantiation of an agent population, allowing the agents to interact, and monitoring what happens [Azar et al., 2010]. In the context of the behavior research in buildings, behavior models can be constructed from existing behavioral theory and empirical data [Macal et al., 2010], BDI (Belief-Desire-Intent) model for rational agent [Wooldridge, 2000], or a complete bottom-up approach that dismisses existing behavior models, theories, and data altogether.

The power of an agent-based modeling approach, particularly in human behavior research, is summarized below:

- All behavioral aspects of agents can be modeled [Azar et al., 2010].
- Allows for the capabilities to study complex systems by aggregating different functionalities that have previously been distinct (planning, learning, coordination, etc.) [Luck et al., 2003].
- Multi-agent simulation systems allow for different agents to be present in an environment, where they interact (e.g., communicate, cooperate, compete, etc.) and/or participate in joint-decision making, much like in the real-world domain [Luck et al., 2003].
- Addresses the uncertainties of the real world by using techniques such as Bayesian network, fuzzy logic, and rough sets [Ramos et al., 2008].
- Each agent, modeled as an autonomous entity, can actually predict the collective behavior [Bonabeau, 2002].
- It provides a framework for tuning the complexity of the agents, e.g., agent behavior, degree of rationality, ability to learn and evolve, and rules of interactions [Bonabeau, 2002].

The three elements of agent-based modeling (ABM) are: (1) a set of agents, their attributes and behaviors; (2) a set of agent relationship and methods of interaction; and (3) agents' environment [Macal et al., 2010]. The implementation of ABM is possible by ABM toolkits, programming language, and others that function as a computational engine for simulating agent behaviors and agent interactions [Macal et al., 2010].

A typical ABM design process is suggested by Macal and North (2010). First, the process starts with identifying the specific question to be solved. In addition, one should ask how the ABM approach could bring added value to the problem-solving effort. Second, the agents in the model are defined by individual characteristics and/or parameters, e.g., a decision maker, a follower, an active participant, and so on. If the parameters of an agent are simply descriptive, they are called static attributes, while those that are constantly updated in the model are called dynamic attributes. Third, the decisions describing agent environment, behaviors to focus on, and interactions among agents are made. An agent environment specifies all the surrounding forces that could potentially stimulate agent behaviors, e.g., a confined space in a building, thermal conditions, schedules, and so on. Agent behaviors are analogous to the occupant behaviors discussed in the dissertation (and will be elaborated upon in later sections). Agent interaction can refer to the interaction between the environment and agents, which is basically manifested as agent behaviors controlling the environment, as well as the interaction among agents. Next, a decision is made on the deliverables of the ABM, e.g., the data/information obtained or lessons learned from the model results. Finally, there needs to be an experiment component to test and validate the ABM. The process is further investigated in the Methodology section of the dissertation.

2.2.2. Simulating Uncertainties

Human behavior in buildings has commonly been cited as the favorable attribute that explains the gap between the simulated and actual energy consumption data. Nevertheless, due to uncertainties in behaviors, most current simulation research neglects to fully account for realistic occupant behaviors [Zimmermann, 2006]. One of the objectives of the research in the dissertation is to uncover limitations in current practices for human behavior simulation, and to find a methodology that best addresses the limitations. The prerequisite for the effort is the hypothesis that the probability of occupant behaviors is predominantly dependent on the environmental stimulus, such as temperature, wind velocity, light level, and the like. Therefore, if one can make fair predictions of the stimuli and establish a relationship with behaviors, occupant behaviors can also be modeled.

The most prevalent method used to predict uncertainties in building simulation is the stochastic process [Herkel et al., 2008][Page et al., 2008] [Sokolowski et al., 2009].

2.3. Human Behavior Research

One of the main advancements in building simulation is in the area of algorithm development [Malkawi, 2004]. As part of the algorithm development for human behavior research, a particular focus has been invested in establishing the stimulus-behavior relationship [Reinhart, 2004]. As mentioned earlier, this relationship increases the predictability of occupant behaviors as long as the future stimuli are reasonably predicted.

Appendix A outlines the current human behavior research that serves as the framework for constructing the behavior algorithms used in the ABM (agent-based modeling).

From the gathered information, examples of behavior algorithms were constructed, as shown in Figure 2.2. They illustrate the relationship between stimulus (triggers or environmental parameters) and behaviors, along with the effects incurred from the behaviors that affect both the energy consumption patterns and the immediate microclimate where the behaviors take place. While some of the stimulus-behavior relationships can easily be explained by a Boolean statement (e.g., blinds, equipment use, etc.), others (e.g., light use, window use, etc.) borrow causality from existing research, such as the Hunt algorithm or the Lightswitch algorithm for electric light use [Hunt 1979] [Reinhart, 2004]. Apart from having the need to make behavior predictions, the algorithms in Figure 2.2 will be used to validate the bottom-up agent-based model (the methodology used to describe the decision-making process for each agent), which is proposed in the dissertation.

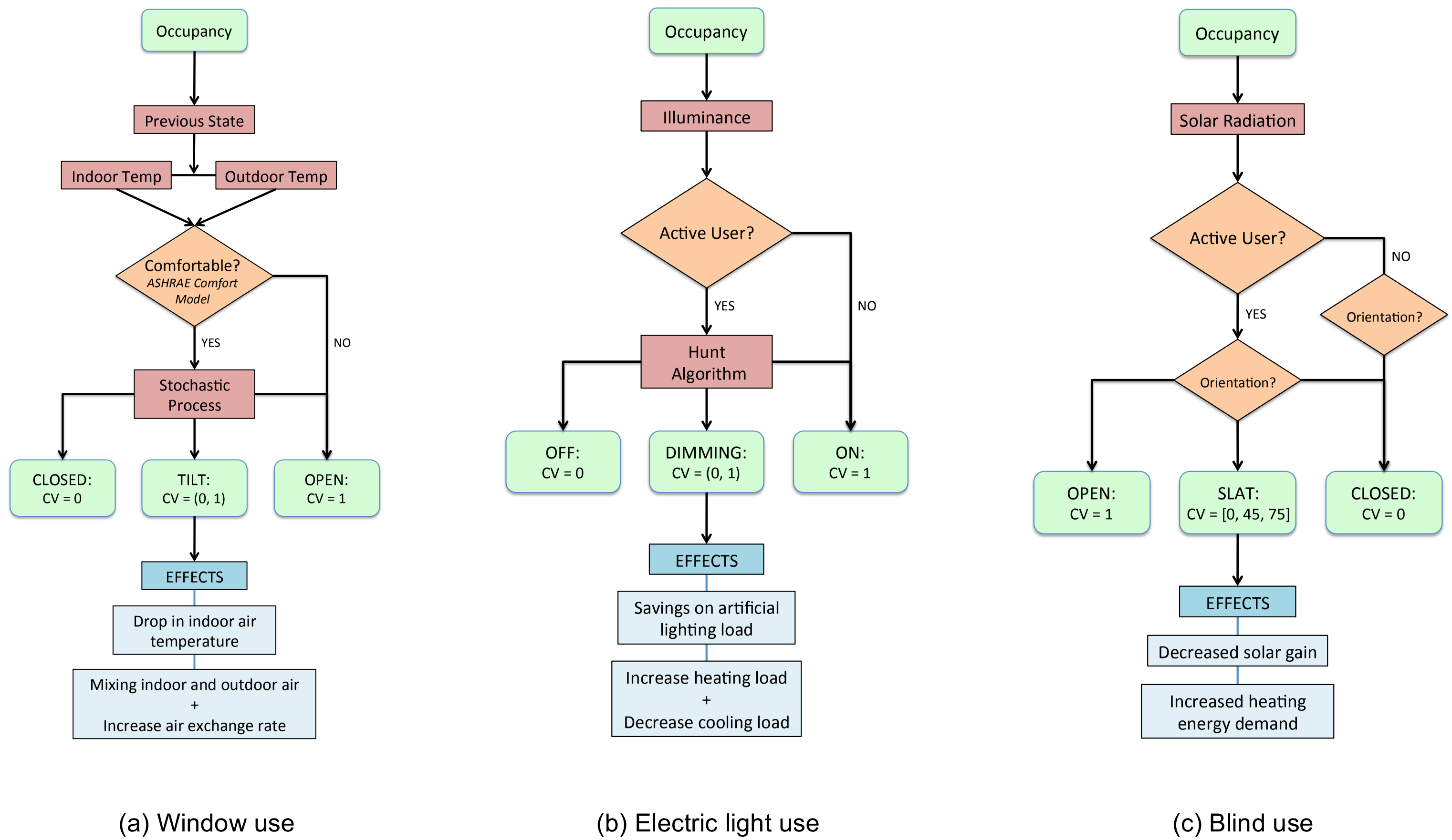


Figure 2.2 Behavior algorithms from existing research

3. METHODOLOGY

The research goal of the dissertation is broken down into two major tasks: predicting occupant behaviors and their interactions with the building, and to quantifying the behaviors into an energy metric. Figure 3.1 presents the core elements of the proposed research. In the diagram, the "Decision Making Process" addresses the first task and the "Behavior to Energy Metric" addresses the second task. The overall process in the far left part of the diagram is analogous to the research objective of the dissertation: for all occupants present in a space, predict behavior decisions, calculate energy implications of the behaviors, and use the findings to increase the overall simulation accuracy. The two tasks of the research are diagrammatically outlined under the "Theoretical Background," and the "Computational Strategy" explains how each process is implemented computationally.

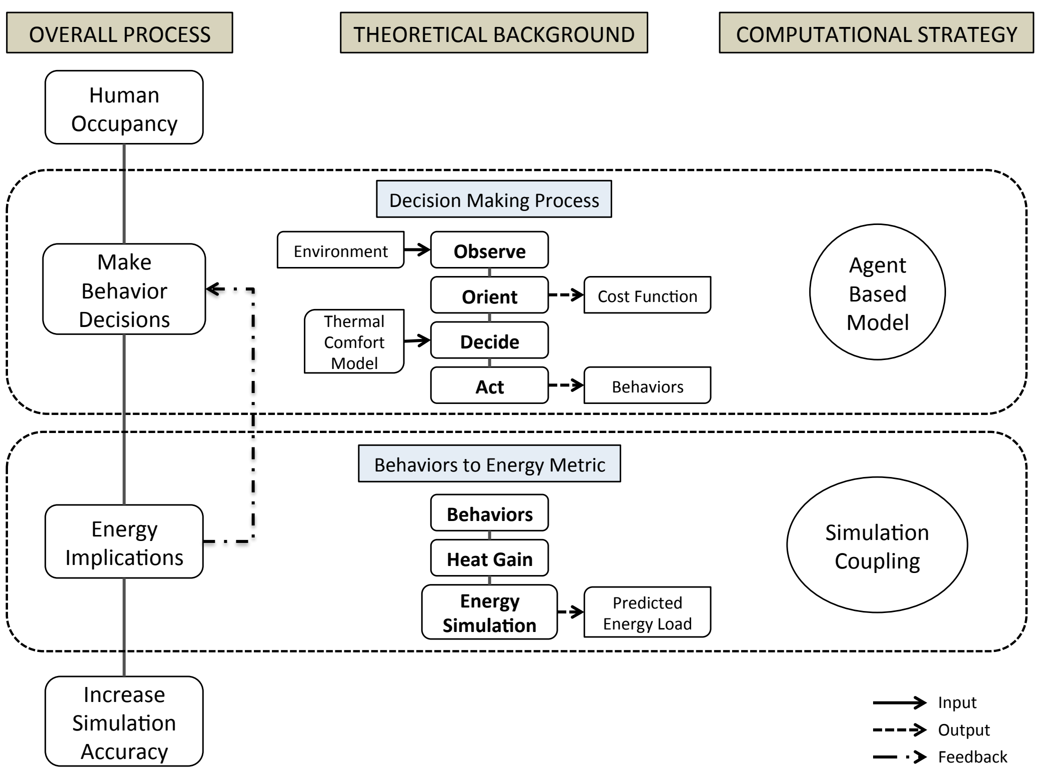


Figure 3.1 Core elements of the research

The methodology applied for the decision making process in Figure 3.1 is through the "Agent-Based Modeling (ABM)" approach (elaborated in Section 3.3). The OODA (observe, orient, decide, and act) Loop [Boyd, 1966][Silverman, 2010] has been reinterpreted to explain the concept of the decision making process (or ABM process) implemented in the dissertation:

1. Observe: An agent understands its surrounding, e.g., climatic conditions and given space.

2. Orient: An agent evaluates its agent parameters (Section 3.3.2) and calculates cost for behavior options (Section 3.3.3).

3. Decide: Based on its level of comfort and the calculated cost, an agent makes behavior decisions to address comfort dissatisfaction.

4. Act: An agent communicates with an external simulator to calculate the behavior impact on energy use and comfort level.

The last component of the OODA Loop is achieved by "Simulation Coupling" in Figure 3.1 (elaborated in Section 3.4). The goal of the simulation coupling is to capture how agent behaviors influence the internal heat gain in a space that can significantly affect the overall energy consumption of the building by having an external building energy simulator to account for the behavior changes made by agents.

This section explains the research process in detail, along with how each step in the research process is compared with the current simulation practice to highlight the shortcomings of current approach and how the proposed methodology mitigates the shortcomings.

Occupant behavior can have multiple connotations in the built environment. Section 3.1 discusses how 'behavior' is defined and used throughout the dissertation. Section 3.2 presents the human behavior model, which primarily investigates the means to measure and quantify the behaviors identified in Section 3.1. The goal is to find a causality that is robust enough to make behavior predictions in buildings. Section 3.3 deals with agent-based modeling, which is a new approach in building simulation for modeling occupant behaviors. Finally, section 3.4 presents a simulation coupling method that integrates all of the components in Figure 3.1 to ultimately increase building energy simulation accuracy.

3.1. Human Behavior in Buildings

According to the Occupant Indoor Environment Quality (IEQ) Survey of existing buildings, ‘Acoustics’ and ‘Thermal Comfort’ have historically been the top two categories with the largest occupant dissatisfaction[1]. In particular, one of the most frequently recurring occupant comments indicates that most occupants are ‘too cold in the summer’ in office spaces, referring to the fact that a lack of consideration for occupant comfort results in the waste of unnecessary cooling energy. The ‘behavior’ studied in the dissertation, therefore, is directly connected to any act of control mitigating the thermal environment to maintain the level of satisfactory comfort, this resonating with the adaptive comfort model mentioned in the previous section.

The behaviors occur when multiple stimulants trigger the occupant to either interact with one or more building systems or change his/her clothing or metabolism levels. Building systems include operable windows, thermostats, sunshades (or blinds), and others that have impact on the energy uses once they are adjusted and/or controlled. Figure 3.2 illustrates the concept of the ‘behaviors’ defined in the dissertation, and their relations to building systems, along with how the notion of ‘behaviors’ has evolved in building simulation development. For the theoretical framework in Figure 3.2, the *reasoned action model* is used for measuring and quantifying behaviors, which explains the stimulus-behavior relationship (this is elaborated in Section 3.2).

[1] Survey of 550 buildings with over 60,000 respondents (as of Oct 2010) conducted by the CBE at UC Berkeley. The core survey categories are the following: Office Layout, Office Furnishing, Thermal Comfort, Air Quality, Lighting, Acoustics, and Cleaning/Maintenance.

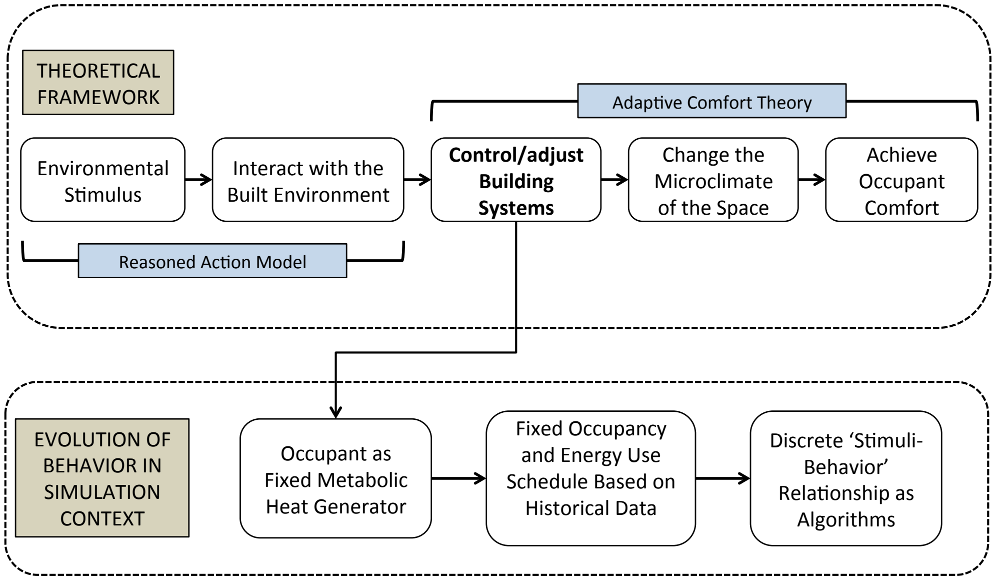


Figure 3.2 Definition of behavior used in the dissertation

The occupant interaction in the built environment, i.e., occupant behavior reflected as some control/adjust of building systems, and the effort towards achieving occupant comfort are based on the Adaptive Comfort Theory. In the past, building simulation programs have accounted for behaviors with varying levels of detail, with respect to the computing capabilities of simulation development. As part of the thermal calculations, behavioral influences had been reduced to solely the number of total occupants, regarding occupants as fixed metabolic heat generators [Newsham, 1994]. The next generation of behavior simulation had included schedules – e.g., occupancy, lighting use, equipment use, etc. – but failed to accurately portray real world behaviors, as the schedules were fixed, deterministic episodes based on historical data [Mahdavi, 2001]. Only recently, a discrete 'stimuli-behavior' relationship in the form of algorithms has emerged to predict certain occupant behaviors – e.g., daylighting use behavior with Daysim [Reinhart, 2004]. The dissertation aims to contribute to furthering the evolution of simulating behaviors by increasing the simulation capabilities to predict real-world occupant behaviors in buildings.

3.2. Human Behavior Modeling

Human behavior modeling is mainly concerned with explaining the relationships between the environmental stimulants and building occupant behaviors. This can be achieved in three steps: occupant behavior measurement, quantifying the measured data on occupant behaviors, and constructing a mathematical model for behavior prediction. The following sections introduce the theoretical background and survey approaches to accomplish the three steps, which will serve as the foundation for simulation studies throughout the dissertation.

3.2.1. Simulative Model

A simulation process requires a robust mathematical model – e.g., a utility function in agent-based modeling – deduced from a widely accepted theoretical framework in order to capture the physical, psychological, and social behaviors of the entity that it wants to mimic [Zeigler et al., 2000]. The same rule applies to the need for an objective function in order to expedite an optimization process in most building related researches [Wang et al., 2005]. However, when the existing references are not substantial enough to construct a feasible model, one has to rely on a data-driven empirical research to construct a bottom up model that suffices as a 'plausible rule of agent behavior' [Epstein, 1999]. In order to pursue this task, the dissertation adopts the four basic levels of knowledge about a system recognized by Klir, in Table 3.1, which resonates with the system hierarchy of most simulation systems structure.

Table 3.1 Four basic levels of knowledge

Level	Name	Content
0	Source	A portion of the real world that we wish to model and the means by which we are going to observe it.
1	Data	Database of measurements and observations made for the source system.
2	Generative	Ability to recreate this data using a more compact representation, such as formula.
3	Structure	Components (at lower levels) coupled together to form a generative system.

Human behavior models in the context of simulation studies typically refer to Level 2 of the above classification [Zeigler et al., 2000], while the research presented in the dissertation encompasses all the levels at different scales. Hence, a generic human behavior model is to be deduced from the *measurements* and *observations* of phenomena such as building occupant behaviors, their interventions on thermal environment and the impact on the overall energy uses, etc.

The development of the model begins with quantifying behaviors into some measurable metric (information or database). Since behavior is a synthesis of action, target, context, and time [Fishbein et al., 2010], one can easily assimilate behaviors with some form of an observable action that is incurred from a function of multiple decision-making variables. As an exercise, an influence diagram of the research objective and the behavior components (action, target, context, and time) are overlaid in Figure 3.3. According to the diagram, 'context' and 'time' components are decision variables that are predetermined, along with the 'target', which is an objective variable. Therefore, the only uncertainties that remain are the chance variables, or the 'action' component of behavior, and a general variable, or the energy demand. This is a reassuring correlation that justifies the fact that a certain behavior can be reduced to the very measurement and observation of the action that is being performed (because the general variables are a direct

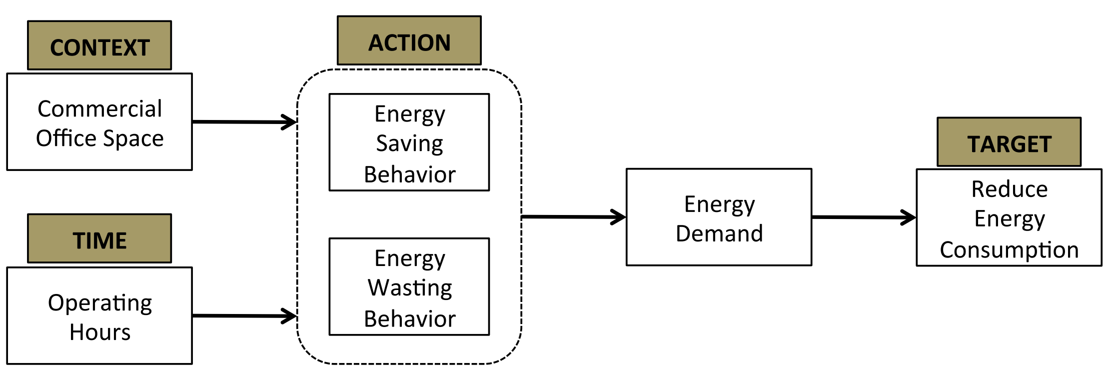


Figure 3.3 Influence diagram of research objective and behavior components

consequence of the chance variables). In short, the main effort in the human behavior model construction simply involves accounting for the actions, within the boundaries of context and time, which have implications on the target.

The goal of the human behavior model is to predict future behaviors. Behavior prediction stems from a collection of behavior measurements with the following assumptions from the literature [Fishbein et al., 2010][Fishbein et al., 1975].

- Human social behavior is determined by a relatively small number of factors, which makes the prediction of behavior not that difficult.
- Since conducting direct observation for a behavioral category is virtually impossible, much of social science research relies on self-reports.
- When proper precautions are taken, self-reports of behavior can be quite reliable and valid – perhaps no less so than direct observation of behavior.
- Theory suggests that intention is the best single predictor of behavior but that it is also important to take skills and abilities as well as environmental factors (e.g., behavioral control) into account.

3.2.2. Reasoned Action Model

The principal theory adopted in the dissertation for behavior measurement is the reasoned action model developed by Fishbein and Ajzen. Figure 3.4 shows a simplified schematic process of behavioral prediction, which is rooted in the idea that 'human social behavior follows reasonably and often spontaneously from the information or beliefs people possess about the behavior under consideration' [Fishbein et al., 2010]. As shown in Figure 3.4, the beliefs associated with a given behavior are distinguished as follows:

- Behavioral beliefs: Beliefs about the positive or negative consequences they might experience if they performed the behavior (outcome expectancy).

- Normative beliefs: People form beliefs that important individuals or groups in their lives would approve or disapprove of their performing the behavior as well as beliefs that these referents themselves perform or don't perform the behavior in question (perceived norm).
- Control beliefs: Beliefs about personal and environmental factors that can help or impede their attempts to carry out the behavior (high/low self-efficacy).

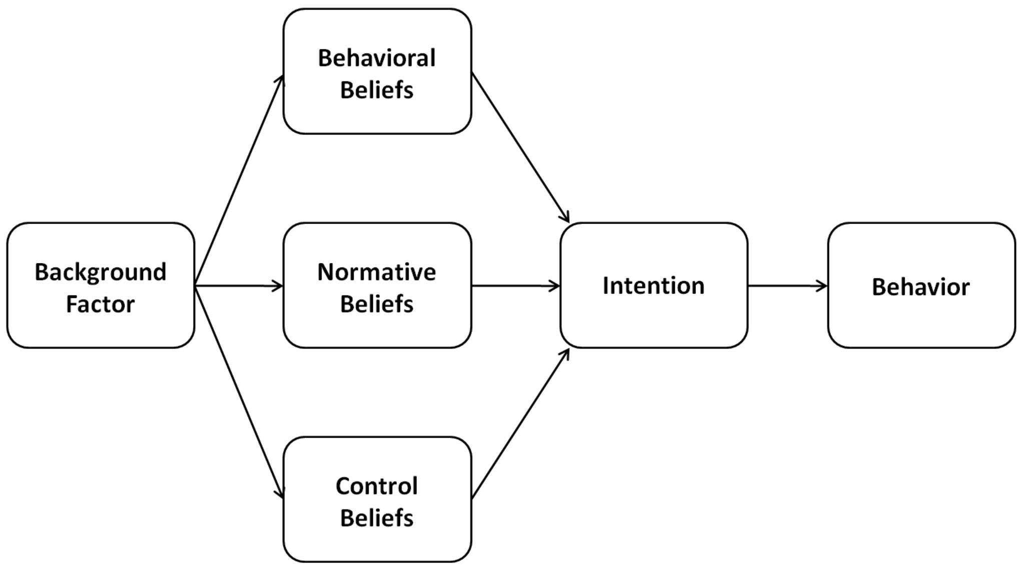


Figure 3.4 Schematic diagram of the Reasoned Action Model

Once the beliefs toward a certain behavior are formed, they are believed to lead the formation of a behavioral intention, or a readiness to perform the behavior. As a general rule, a favorable attitude, a positive perceived norm, and a greater control toward a behavior contribute to strengthening the intention to perform the behavior. However, the relative importance or weight of these three determinants of intentions is expected to vary from one behavior to another and from one population to another [Fishbein et al., 2010].

One issue that emerges in applying the reasoned action model for the research is the uncertainties and/or scope of the behavior itself. Unlike most social science studies – where a single, deterministic behavior, such as the behavior of using birth control pills or condoms, exists – the behaviors that are interventions of thermal environment have not been clearly documented. As a matter of fact, limited behavioral research has been done looking at lighting uses [Bourgeois et al., 2006], and window shading or opening windows for passive systems [Lindelöf et al., 2006]. On that note, one of the important prerequisites of constructing a human behavior modeling is to identify and predict all behaviors that have positive/negative impact on energy uses.

To address the limitations, the dissertation utilizes the existing literature on human behavior research, which will be augmented by the survey methods used in the reasoned action model to identify the most prominent behaviors in buildings. The importance or weight of individual behavior attributes will be used to finalize the behavioral model. Further studies will quantify the energy implications of individual behaviors. One of the assumptions is that the total effect of each

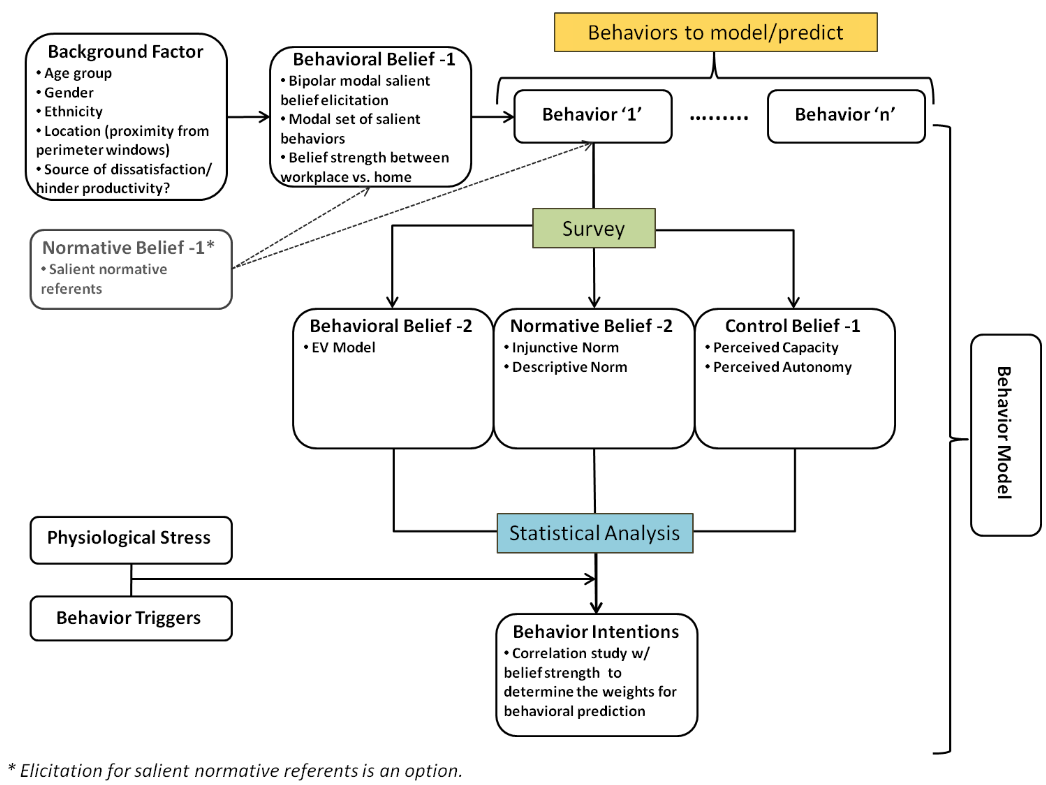


Figure 3.5 Process diagram for human behavior model construction [Fishbein et al., 2010]

behavior can either be positive or negative. Ultimately, the trade-offs between the predicted behaviors on energy use will be calculated.

A detailed process for the human behavior model construction, which is an extension from the reasoned action model shown in Figure 3.4, is illustrated in Figure 3.5. As seen in the process diagram, there are multiple layers of information that are indicative of behaviors – intentions, components of the reasoned action model (behavioral, normative, and control beliefs), and specific sub-beliefs – which are either assumed or surveyed. The statistical analysis is mostly concerned with correlation studies between the behavioral information and the actual behavior occurrences, and thus, defining the behavior intentions. Although estimating relative weights of a predictor variable in multiple regression is the most straightforward method used in the field, the literature suggests that there is no single solution and no 'best' solution is likely to exist as individual project may inevitably incur unique issues/shortcomings [Johnson, 2000][Webb at al., 2006]. Therefore, both the data-mining process and finding statistical significance are beyond the scope of the dissertation, which will instead cover the implementation of the survey and collecting raw data for later analyses. The following three sections explain components of the process shown in Figure 3.5.

The agent-based modeling in the dissertation is intended for a typical commercial building (offices and communal spaces) with the building occupants as the target audience. The reasoned action model recognizes the importance of background factors, as shown in Figure 3.5, which are variables that potentially influence the beliefs of people: individual (personality, mood, emotion, values, stereotypes, general attitudes, perceived risk, and past behavior), social (education, age, gender, income, religion, race, ethnicity, and culture), and general information (knowledge, media, and intervention) [Fishbein et al., 2010]. Identifying relevant background factors can lead to better understanding the determinants of a behavior [Petraitis et al., 1995], even though the direct connection between background factors and beliefs has not been firmly validated [Fishbein et al., 2010]. Nevertheless, the dissertation chose the factors that are believed to have influences on the perceived experience in buildings: occupant location (proximity to windows, interior zone, shared/private office, and perimeter zone), age, gender, ethnicity, knowledge, and general attitudes.

Unless there are means for direct behavior observations to measure behaviors, the best alternative is to simply ask the person using a free-response format [Zajonc, 1954]. An elicitation study seems like a promising approach, asking respondents[2] to describe a list of behaviors that resonate with comfort and energy savings. This is similar to producing the modal set of salient beliefs in the reasoned action model [Fishbein et al., 2010], and could actually be the set of potential behaviors that would be addressed in the dissertation. The objective of the elicitation study is to get a quick sense of the core issues that best address the research question in the dissertation, and ultimately to use the responses from the elicitation survey as a foundation for constructing the general survey questionnaire. The primary questions asked would be as follows:

- If we wanted create energy savings in the workspace, what specific actions do you think we could reasonably ask employees to do in order to accomplish this, whether or not you personally would want to do it?
- If we were to feel thermal discomfort in the workspace, what specific actions do you think we could reasonably do in order to accomplish this, whether or not you personally would want to do it?

Along with the core questions, it would also be advantageous to elicit some salient beliefs on the general attitudes toward energy savings. However, since the act of energy savings is inherently positive, the more meaningful questions could be asked to gauge the willingness for different domains:

[2] The respondents for the elicitation study do not have to match the occupants of the building studied.

- *In general, how willing would you be to partake in energy saving measures in your workplace?*
  not at all willing (1) (2) (3) (4) (5) (6) (7) extremely willing
- *In general, how willing would you be to partake in energy saving measures in your home?*
  not at all willing (1) (2) (3) (4) (5) (6) (7) extremely willing

Despite the caution against using focus groups in eliciting the salient beliefs or behaviors [Fishbein et al., 2010], the lack of understanding in building systems and energy savings might result in responses with inconsistencies. The last question about technical familiarity will help to select a competent focus group, whose answers will eventually help to construct the general survey (shown as “Survey’ on Figure 3.5) administered to a larger target audience:

- *My understanding of building systems and/or sustainability compared to an average person is*
  extremely bad (1) (2) (3) (4) (5) (6) (7) extremely good

From the elicitation study, two pieces of information can be collected: a set of salient behaviors that have implications for thermal comfort and energy use, and the attitude strength in performing the energy savings behavior in residential versus commercial buildings. While the latter can be used as a justification for the selection of one building typology over the other, the salient behaviors are essential to further developing the questionnaire that will measure and collect data for the human behavior model. The questionnaire will ask about the three belief-behavior relationships mentioned in the reasoned action model (see Figure 3.4), along with questions regarding some background information. For example, let’s assume that the following salient behaviors, which have the greatest impact on overall thermal comfort level and energy use, are chosen to be included in the questionnaire:

1. *Adjust clothing*
2. *Use personal heater/fan*

3. *Open the windows*
4. *Use the interior shades*
5. *Adjust the thermostat*

A typical questionnaire would require a single set of questions for a single behavior. However, the case in the above circumstances would require five sets of questions in one questionnaire. Therefore, it is crucial that questions for each category are limited to a reasonable number so as to avoid a loss of motivation among respondents.

As an example, a set of survey questions for the salient behavior for window use (note that the sample questionnaire adopts bipolar scoring as suggested in the literature [Fishbein et al., 2010]) is presented in Appendix B.

3.3. Agent-Based Modeling

The previous section briefly introduced the concept of agent-based modeling (ABM) and some of the capabilities that underscore ABM as a promising ‘methodology’ in studying human behavior. ABM is typically defined as either a simulation tool, programming language, prediction model, etc. [Silverman, 2010][Macal et al., 2010][Luck et al., 2003][Epstein, 1999]. Needless to say, the choice of one ABM over another will be determined by the scope of the research and questions asked. The goal of this section is to present the ABM used in the dissertation, which basically helps to address the following research questions in regard to human behavior in buildings:

- How is ABM different from existing behavior simulation methods? And what would make ABM approach better than the current simulation approach?
- Other than the thermal stimuli, how important are the occupants’ social interaction and their learning mechanism on making behavior decisions in a space?

3.3.1. ABM Mindset

The nature and scope of ABM are different among disciplines. But instead of just focusing on the technology side of ABM, the research in the dissertation first highlights the mindset of ABM, which consists of describing a system from the perspective of its constituent units [Bonabeau, 2002]. Even at the simplest level, if an ABM consists of agents and the relationship between them, there could be valuable findings about the system as a whole, i.e., a system that it is trying to emulate [Bonabeau, 2002]. The questions that have paramount importance in choosing the scope of ABM are, “do we want the agents to perform tasks like humans?” or “do we want the agents to perform better than humans?” As an effort toward answering the first question, the dissertation starts with the simplest ABM to think about occupant behaviors from the occupant perspective. For example, a human-like agent could make behavior decisions solely on its level of comfort in a given space. On the other hand, an agent that performs better than humans could potentially make behavior decisions based on comfort level, but in the most energy-efficient way possible. The dissimilar agent characteristics are tested in the simulation experiment (refer to Section 4.3).

The current building simulation process makes it hard to incorporate the ABM process, because the behavior decisions are predominantly driven by the building, or its mechanical systems, as a whole. In other words, occupant behaviors are not representative of actual real-world behaviors, but are abstracted, oversimplified, and predetermined. As an example, a simulation process for window use behavior is introduced, along with the limitations that neglect to fully reflect the reality. Figure 3.6 is a diagram explaining how existing simulation programs, such as Energy Plus, handle behavior-related input information, compared to ABM processes proposed in the dissertation.

Prior to explaining the different simulation processes, it is important to highlight that both cases in Figure 3.6 start with understanding the ‘Human Occupancy.’ Occupancy is simply the ratio of total occupants that are present in the given simulation space. The connotation of occupancy in the ABM process is quite different from that of the existing simulation process, which will be discussed in detail in Section 4.1.

Currently, one of the most common ways to account for human behavior and/or feedback is through occupancy and operation schedules. In the existing simulation process in Figure 3.6, operation schedules for occupancy, equipment, lighting, ventilation, and others are how the simulation program interprets occupants' enter/exit/occupy behavior, equipment use behavior, lighting use behavior, window use behavior, etc. These schedules are mostly referenced from historical data or building standards, which are predefined and fixed throughout the simulation process. The use of deterministic operation schedules is one of the major limitations of the existing simulation process as it lacks the capabilities to capture the dynamic characteristics of an actual operating building. One can easily infer that the energy implications from the existing simulation process will lack in accuracy; hence, in order to enhance the robustness of simulation programs, true to life predictions of occupant behaviors are necessary.

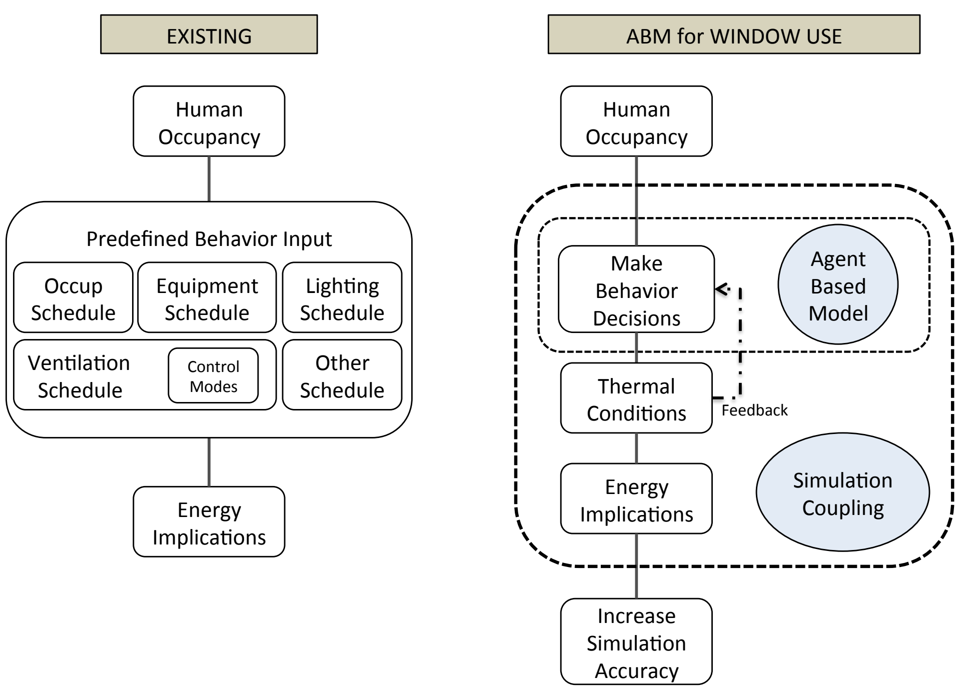


Figure 3.6 Comparison between existing and proposed ABM process for simulating window use behavior

The new simulation approach using ABM, however, follows a very different process. The ABM component in Figure 3.6 is grounded on the notion that a group's collective behavior is understood through observations of individual behaviors. In addition, ABM captures the immediate thermal changes incurred from individual behavior decisions, which not only affect the overall energy performance but also the individual agent's future behavior decisions. The main characteristics of the ABM process that distinguish itself from the existing process are as follows:

- The process can account for the dynamic environmental changes – e.g., temperature, air speed, light level, and others – that are consequences of agent behaviors.
- The process encourages constant feedback to be exchanged among agents, behaviors, and environment. The availability for the feedback loop is greatly provided by simulation coupling, which will be discussed in Section 3.4.
- Contrary to making system-oriented behavior decisions – for example, only considering temperature data from mechanical systems (setpoint temperature) and space as a whole (zone mean air temperature) – the process achieves agent-oriented behavior decisions by focusing on the thermal conditions close to the agent, which truly aligns with the ABM mindset.

The first two characteristics are elaborated upon through the simulation experiment in Section 4, while the last one is done here.

In a naturally ventilated space, for example, thermal conditions of a space are regulated primarily by the occupant through the opening and closing of windows [ASHRAE, 2004]. As discussed in previous sections, environmental stimulants dictate most of the behaviors observed in buildings. Going back to the window use behavior in Figure 3.6, various temperature data (outside dry bulb, zone air, cooling/heating setpoint, etc.) are known to be the main drivers for the behavior [ASHRAE, 2004][DOE, 2011]. The existing simulation process for window use behavior is a system-oriented decision-making process, while the ABM process proposed in the dissertation strives to take the comfort-related temperature of individual agent into consideration for making window use behaviors. The effort acknowledges the diversities in behavioral patterns, much like in reality, and tries to capture agent-oriented behavior decisions. The specifics of making behavior decisions, both existing and ABM processes, are further discussed in the next sections.

3.3.2. ABM Decision-Making Process

The decision-making process in ABM can be constructed from a mixture of various references: existing literature, human behavior model (Section 3.2), heuristics, personal experience, etc. However, the initial decision-making process of the ABM in the dissertation starts as a bottom-up process that excludes all existing behavior models and statistics in the literature, while trying to mimic an actual person in buildings. Figure 3.7 is a detailed state-transition diagram of the agent decision-making process and simulation coupling, which constitute the main ABM function.

At time *t*, the decision-making process is initiated when an agent is present in the space. The ABM in the dissertation is designed to be an open-architecture program that accepts various user input information (denoted as “Given” in Figure 3.7), so as to allow the users to customize the ABM for different purposes (e.g., different climates, building typologies, agent goals, and so on). A full list of the user input information is summarized in Appendix C, which includes information about simulation control (number of agents, simulation time, and others), agent characteristics (clothing/activity levels and initial behavior beliefs), and building systems (equipment and blind types). This information is needed for an agent to *observe* its surrounding, such as the environmental parameters and potential behaviors. Environmental parameters consist of weather data – air temperature, radiant temperature, humidity, air speed, etc. – that help to determine agent comfort level in the space. Potential behaviors refer to building systems that are connected to agent behaviors, e.g., windows, light switch, thermostat, personal fan/heater, doors, and so on.

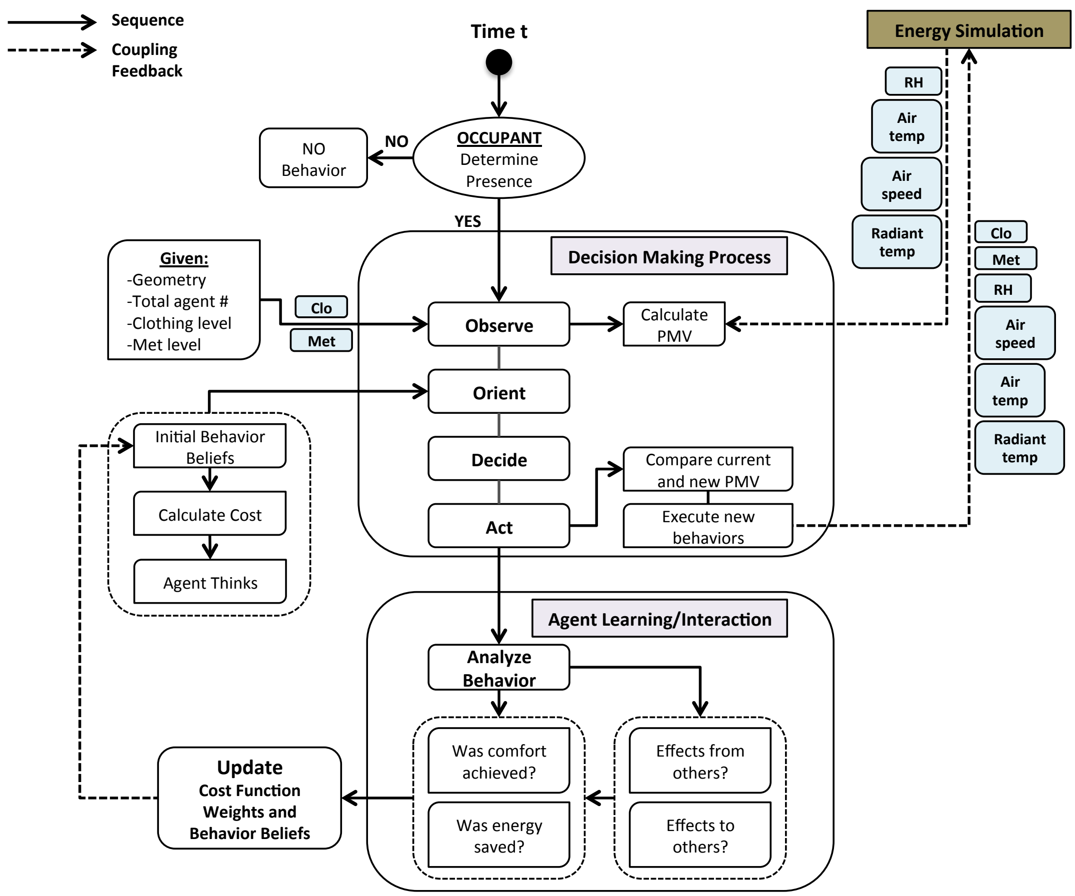


Figure 3.7 Main ABM function (decision-making process and simulation coupling)

An agent determines its comfort level by calculating Fanger's PMV model, as the model agrees well with most climates in the world – in buildings both with and without HVAC systems (Fanger et al., 2002). The calculation of PMV consists of several parameters related to the weather data, clothing level, and activity level of an agent: clothing value, metabolic rate, air temperature, mean radiant temperature, relative air velocity, relative humidity, and water vapor pressure. Some of these parameters are directly linked to the controlling of agent behaviors, as shown in Figure 3.8. While the clothing levels (three levels for cold, hot, and transition seasons) and activity level are user-defined, the rest of the PMV parameters in Figure 3.8 are imported from an external simulator (EnergyPlus) via simulation coupling. Appendix D illustrates how each of the PMV parameters is understood by agents and controlled in EnergyPlus.

Behavior	PMV Parameter
Window	Air speed
Clothing	clo
Activity	met
Fan/Heater	Air temperature
Blinds	Radiant temperature Light level
Door	Air speed

Figure 3.8 PMV and agent behaviors

An agent *orients* itself by calculating the cost function to think about behavior options to achieve agent goals. The cost function (Section 3.3.3) is an equation comprised of agent characteristics, information about building systems, agent behavior beliefs, and behavior belief weights to calculate the cost for each behavior. The cost will determine the likelihood that a behavior will be executed by an agent. In other words, an agent can sort all behaviors by cost (from maximum cost to minimum cost), which is indicative of an order of preference for behaviors. Along with the preference for behaviors, behavior options also encompass the number of behaviors to consider. This is closely related to an agent's current comfort level as part of the PMV calculation. For example, if an agent is extremely dissatisfied with the comfort level (PMV ≥ 2.5 or PMV ≤ -2.5), it can consider up to four different behaviors to mitigate the discomfort. Likewise, for a marginal discomfort level, an agent can consider up to three different behaviors, and so on.

The goal of an agent is to be comfortable in a given space, as the level of occupant comfort is highly correlated with behaviors observed in buildings [Humphreys and Nicol, 1998]. As commonly seen in post-occupancy surveys, thermal and visual discomforts have the biggest impact on the comfort level. If an agent feels uncomfortable in the space, it needs to mitigate the situation by some form of interaction with the built environment [Newsham, 1994]. The ABM keeps track of previous agent comfort levels, or PMV values, which are used to determine how the behaviors are executed. If the comfort level at time *t-1* is higher than time *t*, an agent will *decide* to change behaviors – a set of behavior options from the last process – so that the comfort level would increase at time *t+1*. For example, if agent discomfort from being cold increased from the last timestep, the agetn can turn ON the heater and CLOSE the windows, while those behaviors could be to turn OFF the heater and OPEN the blinds when the agent discomfort decreased significantly.

Finally, all the behavior decisions made by an agent are communicated to an external simulator to calculate behavior impact on energy use, on agent comfort, and on the thermal conditions of the space. This is referred to as the agent *act* process in Figure 3.7, which concludes the "Decision Making Process."

The following sections will elaborate on ABM cost function, agent learning and interaction, and simulation coupling.

3.3.3. ABM Cost Function

An agent cost function is a mathematical equation that an agent calculates to make behavior decisions. The cost function adopts the mathematical model from social sciences, where the model involves "describing relationship between variables using mathematical concepts" [Jaccard et al., 2010]. The model is intended to be a predictive model where the relationships between the variables could explain future behaviors or phenomena. The dissertation uses a simple linear function, which is one of the most commonly used functions in social sciences, with an error term,

$$f(X) = a + bX + e$$

where a and b are constants, X is a variable, and e is an error term [Jaccard et al., 2010]. The inclusion of an error term is to allow for some degree of randomness, which is an important characteristic of a probabilistic or stochastic model [Jaccard et al., 2010].

Typically, defining the constants, variables, and error term for the model construction, along with their causal relationship, starts from a general framework from existing research. The relationship in the causal model is verified by selecting the target audience, collecting survey results, and conducting statistical analysis of the survey results [Nguyen et al., 2013]. The behavior decision-making process in the dissertation is based on the reasoned action model. Taking into account the absence of consensus about the relationship between the reasoned action model and building occupant behaviors in the literature, the following Figure 3.9 presents potential causal models that offer explanations of the relationship. Since the scope of the dissertation does not cover conducting surveys of actual building occupants, it will assume that the constructs of the reasoned action model have comparable effects on an agent's overall belief on comfort, i.e., (a) in Figure 3.9.

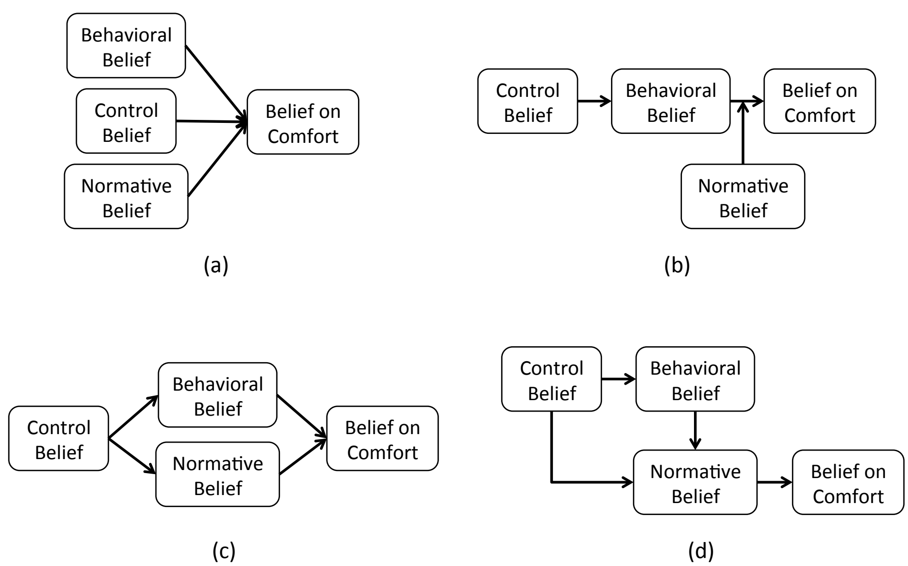


Figure 3.9 Examples of causal model between the reasoned action model and belief on comfort

The ABM in the dissertation is comprised of goal-based agents, which can be defined as agents who 'keep track of the world state as well as a set of goals they are trying to achieve, and choose an action that will eventually lead to the achievement of their goals' [Russell et al., 2003].

The cost function helps an agent to make the optimal behavior decisions to achieve its goal. An agent goal throughout the dissertation has consistently been the level of agent comfort level, i.e., to maintain and/or achieve the comfort level in the space by means of adaptive control, or occupant behavior, which is simply adjusting various building systems [Humphreys and Nicol, 1998]. However, an agent cost function can vary depending on the purposes of ABM, e.g., energy savings, maximum use of natural ventilation, etc.

The initial agent cost function used in the dissertation is expressed as follows:

$$f_{ij}(t) = a_{ij}x_{ij} + b_{ij}y_{ij} + c_{ij}z_{ij} + d_i x'_i - e_{ij}y'_{ij}$$

f_{ij} = Belief towards comfort for agent i *(where* i *= 1, …, n)* and behavior j *(where j = 1, …, m)*

x = Behavioral belief

y = Control belief

z = Normative belief

x' = Characteristics of an agent

y' = Distance from agent to system (optional)

t = Current time

a, b, c, d, e = Respective weight coefficients at time t,

where variables x, y, and z and error terms x' and y' calculate the agent i's overall belief towards comfort for behavior j. The idea is that the bigger the cost f_{ij}, the greater probability that behavior j would be considered by agent i in order to address its comfort level. Therefore, when there are sets of behaviors that an agent is able to control, the agent will calculate the cost function to rank the behaviors from maximum cost to minimum cost. The behavior with the maximum cost becomes the behavior of priority for an agent – i.e., in order to improve its comfort level, the agent will execute the behavior with the greatest likelihood compared to other behaviors. Optimizing the cost function begins with defining the weight coefficients in the above equation. Initial weights can be decided on by a simple survey, as prescribed in the reasoned action model [Fishbein et al., 2010], which can later be validated through case studies and measured data.

3.3.4. ABM Learning and Interaction

Within the ABM process, agent learning and agent interaction are the key features of an intelligent, autonomous agent. The dissertation uses the reasoned action model as a framework to fulfil agent learning and interaction in the ABM, in addition to making agent behavior decisions (in Figure 3.7), as illustrated in Figure 3.10.

Agent learning is achieved through behavioral belief, (a) in Figure 3.10. Behavior impact on comfort (or the effectiveness on comfort) becomes a part of an agent's memory in the ABM. If a certain behavior has a positive impact on comfort, an agent will increase its initial behavioral belief on the behavior, or decrease with negative impact on comfort. The behavior impact on comfort is determined by the changes between the PMV values of time *t* and *t-1*. The increment changes in the behavioral beliefs are as follows – say, $\Delta PMV = abs(PMV_t - PMV_{t-1})$, a=5, b=6, and c=7 (a, b, and c are initial weight coefficients):

- Behavior very effective in comfort: Increase by ($\Delta PMV \times random(0,1) \div a$).
- Behavior moderately effective in comfort: Increase by ($\Delta PMV \times random(0,1) \div b$).
- Behavior barely effective in comfort: Increase by ($\Delta PMV \times random(0,1) \div c$).
- Behavior very ineffective in comfort: Decrease by ($\Delta PMV \times random(0,1) \div c$).
- Behavior moderately ineffective in comfort: Decrease by ($\Delta PMV \times random(0,1) \div b$).
- Behavior barely ineffective in comfort: Decrease by ($\Delta PMV \times random(0,1) \div a$).

- Behavior unchanged: No increment changes applied.

Agent interaction is achieved through normative belief, (c) in Figure 3.10. The normative belief determines how an agent behavior will affect other agents, and vice versa. Those that influence the normative belief are factors like the proximity between agents, agent hierarchy, an agent's perceived norm, and other qualities that establish the social connectivity of agents [Zacharias et al., 2008]. Once established, the agent social connectivity will impact the rate of agent behavior execution. For example, the rate of agent behavior execution would be higher if all agents are of a parallel social status (colleagues), rather than a vertical social status (boss and employers). At each simulation timestep, an agent evaluates the positive or negative feedback on its behavior from others and updates the initial normative belief.

The ABM assumes that the control beliefs, (b) in Figure 3.10, are consistent throughout the year and do not affect in the agent learning or interaction mechanism.

Figure 3.11 is an expanded agent decision-making process linked with the agent learning and agent interaction features. In the agent learning/training diagram in Figure 3.11, an agent can choose different agent goals – comfort or energy savings – to be the criteria for evaluating the behavior effectiveness. The learning process changes/updates an agent's behavioral belief at each timestep, which also updates the cost from the cost function. As a result, the ABM has the capabilities to allow an agent to adapt to the changing climate conditions, because the effectiveness of behaviors toward its goal can vary depending on the season.

In some cases, agents may be bounded by managerial arrangements that may limit certain behaviors, e.g., soliciting the use of daylight so as to minimize the use of electric lighting, as in Figure 3.11. However, these arrangements and the social dynamics of a building are very case-specific and are thus difficult to generalize about. Therefore, the ABM will only underscore the importance and/or potential capabilities of the agent interaction mechanism without further investigating a detailed process. Similar to the agent learning/training in in Figure 3.11, agent interaction can also update the cost from the cost function.

While the changing agent learning and interaction yield a new cost at each timestep, they are assumed to be independent from the cost function optimization.

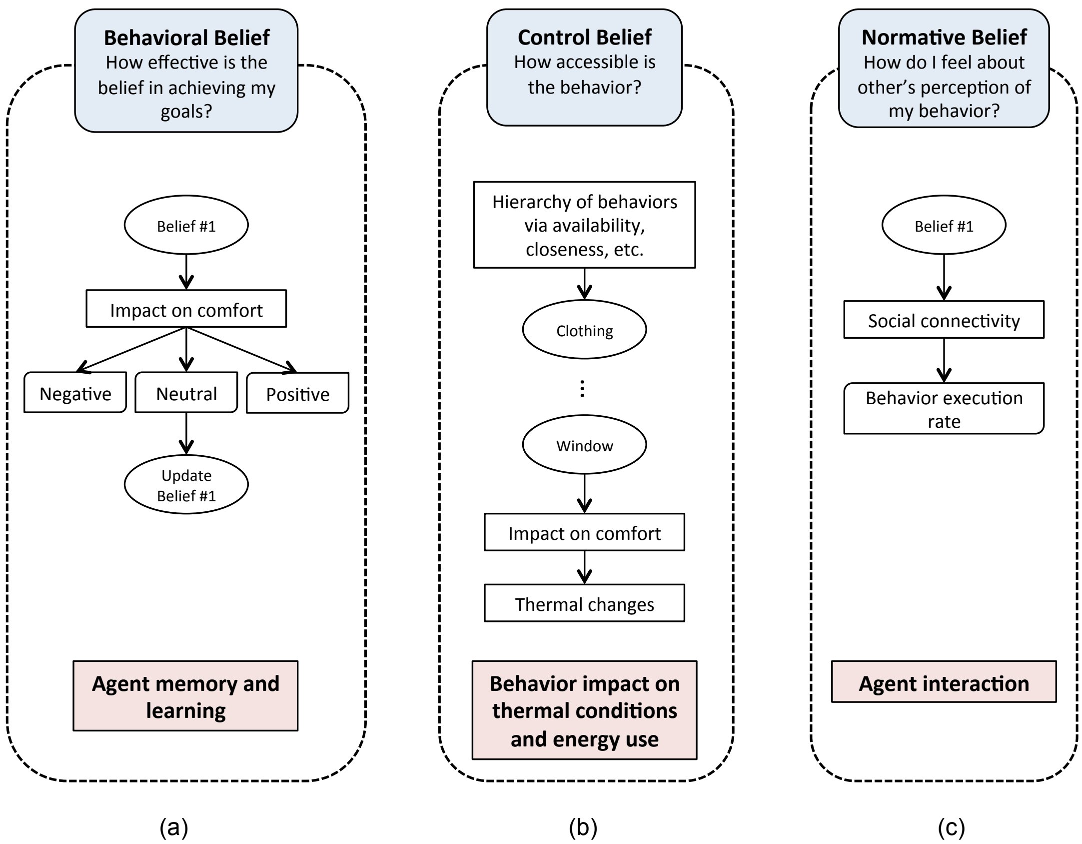


Figure 3.10 ABM interpretation of agent learning and interaction

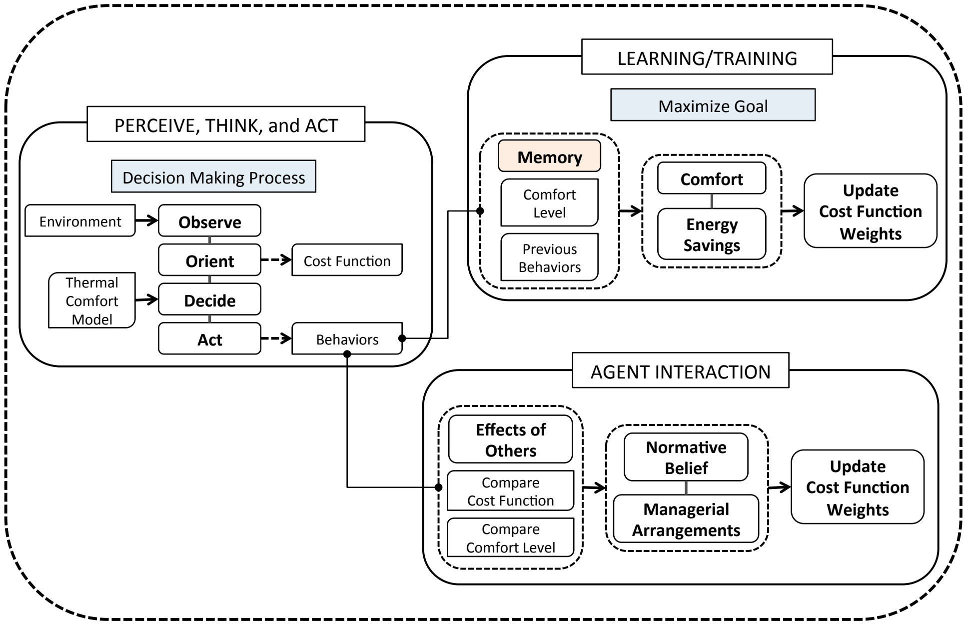


Figure 3.11 Agent decision-making process linked with agent learning and agent interaction

3.4. Simulation Coupling

Once an agent behavior is observed, the ABM uses an external simulator to calculate the changes in the environmental parameters, the agent satisfaction (comfort) level, and ultimately the energy use pattern. The changes are tracked every hour (or otherwise to the specific timestep used in simulation experiments) and reflected in the next hour by updating agent and building system properties. The integration of multiple simulators is achieved through simulation coupling, or by application in which at least two simulators – each solving an initial-value differential or difference equation – are coupled to exchange data that depend on state variables [Wetter, 2010]. The advantage of simulation coupling is that it addresses the need for multiple simulation engines to overcome computational limitations, and ultimately increase efficiency and prediction accuracy of simulation tools [Malkawi, 2004].

The simulation coupling implemented in the dissertation integrates two main simulators: ABM framework programmed in MATLAB and building energy simulation via EnergyPlus (version 7.1).

The actual coupling is available through the BCVTB architecture [Wetter, 2010] and the MLE+ [Truong, 2012]. The Building Controls Virtual Test Bed (BCVTB)[3] is a software environment that allows expert users to couple different simulation programs. For example, the BCVTB allows the simulation of a building and HVAC system in EnergyPlus and the control logic in Modelica or in Matlab/Simulink, while exchanging data between the software as they simulate. MLE+ is an open-source Matlab/Simulink toolbox[4] for simulation coupling with the whole-building energy simulator EnergyPlus. The main feature of MLE+ is that it streamlines the configuration process of linking the building model and the controllers (Matlab) by abstracting the necessary parameters, which reduces setup time and configuration problems[5].

The simulation coupling process for the ABM in the dissertation and the actual ABM codes are presented in Appendix E.

Figure 3.12 illustrates an overview of data exchange as a result of the simulation coupling. The left side of Figure 3.12 is mainly concerned with the ABM decision-making process, i.e., the variables populated by the ABM that are related to specific behavior and their equivalent parameters in the PMV calculation (included in the Matlab *.m* file). The right side is concerned with the EnergyPlus syntaxes (codes) that are direct interpretations of the ABM vocabulary (included in the *.idf* file). In the middle, the common variables for data exchange are shown (included in the *variable.cfg* in Appendix E). An example of the data exchange is graphically represented in Appendix D.

[3] http://simulationresearch.lbl.gov/bcvtb
[4] http://mlab.seas.upenn.edu/mlep/
[5] Detailed manuals for both BCVTB and MLE+ are available online, and hence will not be covered in the dissertation.

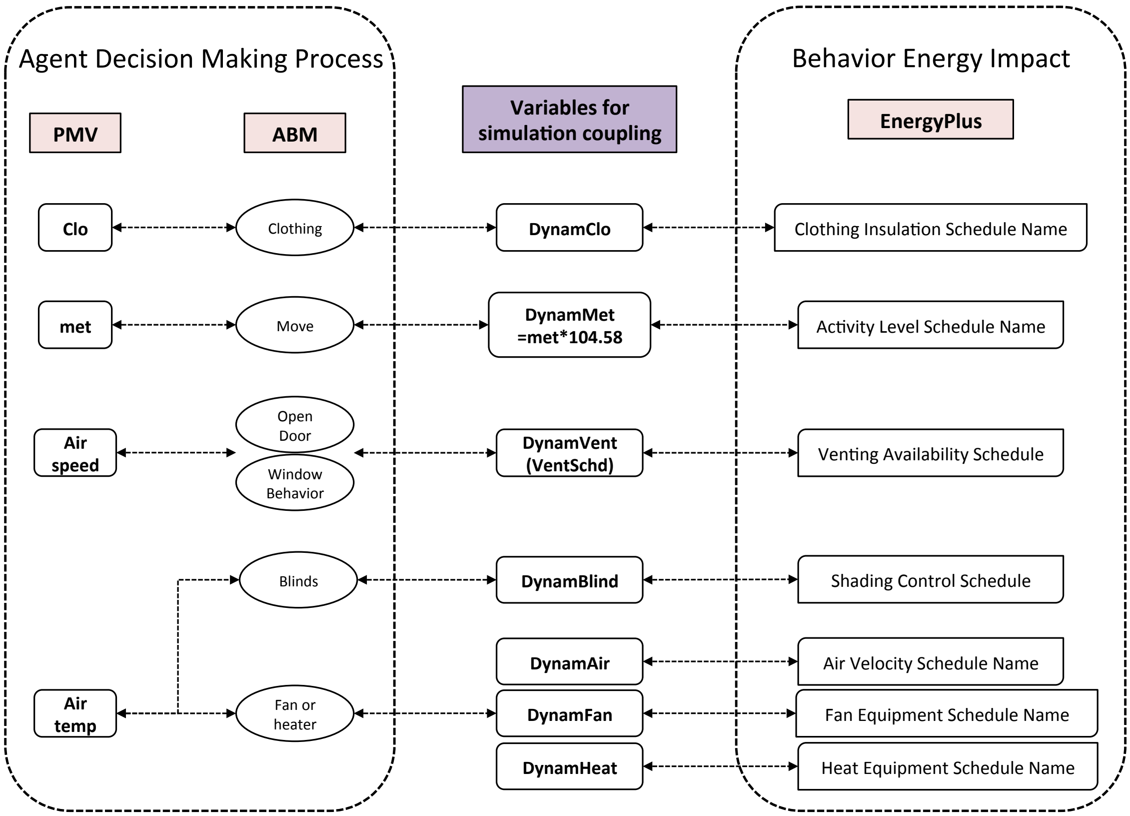


Figure 3.12 Overview of data exchange from simulation coupling (between ABM and EnergyPlus)

An all-encompassing research process that includes the materials discussed in this section is illustrated in Figure 3.13. The experiment and validation components in Figure 3.13 are explained in the following Experiment section.

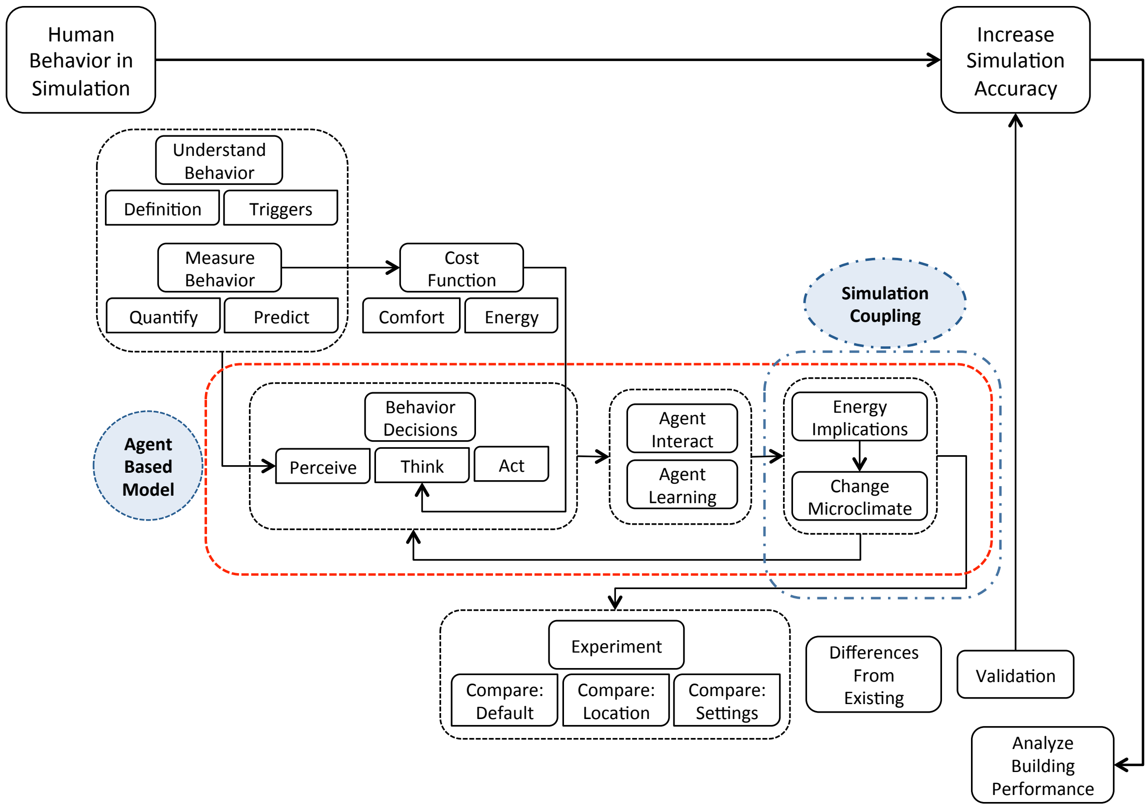


Figure 3.13 All-encompassing research process

4. EXPERIMENTS

This section covers series of simulation experiments that test the ideas and methodology discussed in the dissertation. The sequence of the experiments is designed to prompt questions, and to use the lessons learned as the foundation for conducting the next experiment. Therefore, the experiments presented in this section can be regarded as a progression rather than a discrete set of experiments. First, the experiment in Section 4.1 illustrates how occupant behaviors are simulated in a typical building energy simulation program. The section also uncovers critical limitations of existing simulation programs and tries to address them using the concept of the 'Dynamic Schedules.' Ultimately, it discusses the importance of behaviors and behavioral feedback on building energy use. Second, the experiment in Section 4.2 utilizes the dynamic schedules to simulate a single window-use behavior. To distinguish the pursuit from an existing simulation practice, the experiment introduces an agent-based modeling (ABM) approach to simulate and analyze the behavior impact on comfort and energy performance. Next, the experiment in Section 4.2 expands from a single behavior to multiple occupant behaviors. The experiment is an epitome of the methodology and the research process discussed in previous sections. The experiment strives to come up with a new methodology based on the ABM approach to mimic true-to-life building occupant behaviors, so as to better predict building energy load and increase whole-building energy simulation accuracy. Finally, a series of sensitivity analyses are conducted using the simulation methodology in the previous section to not only learn about emerging behavior phenomena of buildings but also to uncover potential applications for future behavior research.

4.1. Simulating Behaviors through Dynamic Schedules

Although recent studies suggest that occupant behaviors change the energy use in buildings, few have explained the causal relationship between behavior and energy performance. This experiment aims to define building occupant behaviors that have implications for overall building energy performance. A comparison of the internal loads in response to the dynamic occupant schedule was conducted in EnergyPlus to illustrate that the uncertainties of occupant behavior can be an important factor of building energy consumption. In addition, a simulation process that could potentially help to account for dynamic occupant behavior is proposed. The objective of the experiment is to connect the behavioral feedback into the building energy simulation program to increase the prediction (simulation) accuracy, with the aims of enhancing its capability to maximize/optimize energy efficiency.

4.1.1. Introduction

Building simulation programs are becoming increasingly advanced, and much effort has been spent on increasing their prediction accuracy. One of the most frequent criticisms of simulation capabilities found in the literature is the lack of consideration for human behavior and its feedback in the simulation programs [Zimmermann, 2006] [Crawley et al., 2008][Malkawi, 2004]. Some of the limitations that lead to this oversight are due to the complexity and uncertainties of human behavior [Khotanzad et al., 1995] [Mahdavi et al., 2001], and logistical limitations due to computational power and data storage [Somaranthne et al., 2005].

Currently, the most common ways to account for human behavior and/or feedback are occupancy and operation schedules. However, in order to capture the dynamic characteristics of an actual operational building, and thus enhance the robustness of the building energy simulation programs, human behavior and behavioral impact on energy use are essential components in future simulation development [Hoes et al., 2009][Rijal et al., 2007][Dusée, 2004].

Precedent research endeavors had studied the means to simulate specific occupant behaviors – e.g., lighting control [Bourgeois et al., 2006][Lindelöf et al., 2006], operable window control [Rijal et al., 2007], shading control [Reinhart, 2004], etc. This experiment adopts the use of case studies for data collection and the statistical analysis proposed in previous literature. However, it distinguishes itself from prior analyses by addressing the following shortcomings: First, it focuses on fundamental behavioral attributes – not just a single, specific occupant control measure – that are dynamic. It also takes the whole-building energy performance into consideration, with a focus on heating and cooling energy consumption. This is achieved by making better predictions about the building's internal load incurred from occupant behaviors. Therefore, the behaviors mentioned in the experiment encompass not only the aforementioned occupant controls, but also those that significantly affect the microclimate of the workspace.

The goal is to quantify those behaviors into an energy metric, and incorporate them into current building energy simulation programs as part of a *feedback* loop. The experiment focuses on resolving this specific issue by executing the 'Dynamic Schedule' process.

The 'Dynamic Schedule' has two distinct implications. First, the 'Dynamic Schedule' is indicative of the methodology that enables users to link human behaviors and building energy simulation programs, so that each behavior, and its impact on energy use, is accounted for – specifically, during the simulation process for calculating the whole-building energy consumption. And, as a more trivial definition that takes its literal connotation, the 'Dynamic Schedule' is the direct response to the criticism of using oversimplified/predetermined operation schedules (e.g., occupancy, lighting, equipment, and HVAC schedules) in current building energy simulation programs [Mahdavi, 2001] [Yang et al., 2005]. Hence, the 'Dynamic Schedule' rejects such deterministic schedules that are based on historical data, while emulating the actual (dynamic) schedules of an actual operating building.

The two essential prerequisites of the greater human behavior research are identifying the occupant behaviors in an operating building and quantifying the behavioral information into the building energy simulation program. This experiment mainly presents the 'Dynamic Schedule' as a methodology, because it addresses the latter by way of manipulating operation schedules (occupancy, lighting, equipment, and HV AC schedules), where the schedules ultimately reflect the load changes as a result of particular occupant behavior. This is based on the assumption that occupant behaviors identified in the buildings have distinct internal load associated with them. For example, if a behavioral intention of using a personal fan is anticipated, an increase in the equipment load can also be expected; and thus, changes can be made to the equipment schedule to reflect this load difference.

4.1.2. Methodology

Identifying specific occupant behaviors in an operating building is the precursor to making good use of the 'Dynamic Schedule.' These behaviors can be obtained through the behavior measurement methods [Fishbein et al., 2010], which will eventually be incorporated into the 'Dynamic Schedule' process (examples of the behaviors that have the highest probable occurrences in an office environment during the summer/hot months are obtained through a preliminary survey: opening windows; using a personal fan; or adjusting blinds, lights, clothing level, and the thermostat).

A detailed process of the 'Dynamic Schedule' is outlined in Figure 4.1. The objective of the process is to simulate both a realistic occupancy – e.g., a routine meeting, class/training, etc. – and the different occupant behaviors (as identified earlier), which are neglected in current simulation practices, to calculate the impact of behaviors on building energy use.

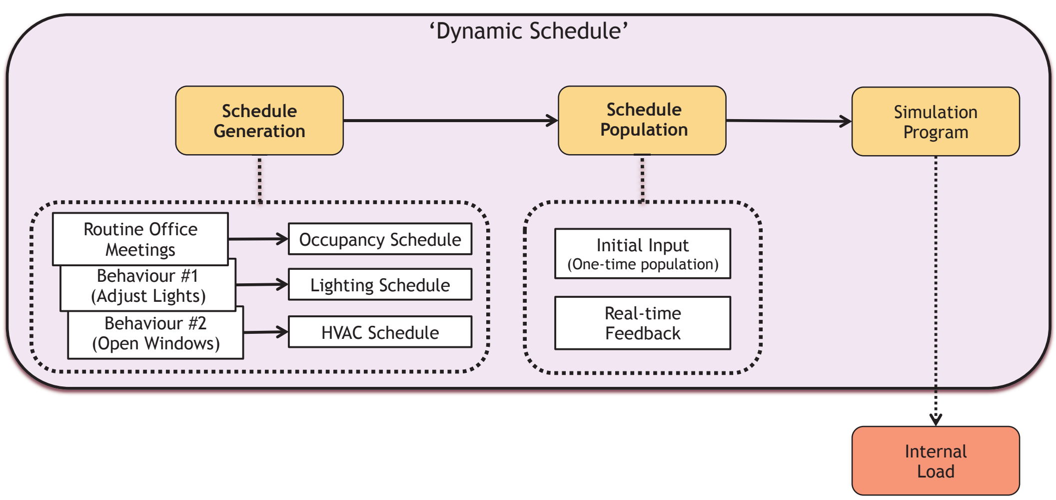


Figure 4.1 A detailed process of the 'Dynamic Schedule' (Lee et al., 2011)

‘Schedule Generation’ explains how various occupant behaviors and occupancies are collected and quantified so that their load changes are interpreted in terms of the operation schedules (occupancy, lighting, equipment, and HVAC schedules). The collective schedules (occupancy, lighting, and HVAC schedules listed under ‘Schedule Generation’ in Figure 4.1) are estimations that are generated by methods explained later. ‘Schedule Population’ refers to transferring this input information, or generated schedules, into the building energy simulation programs. This basically takes the generated schedules and translates them into simulation syntax (or language). ‘Schedule Population’ can be a one-time event, or ‘Initial Input,’ prior to running the simulation. In other words, year-round schedule input information can be defined and used to simulate annual building energy consumption (this is demonstrated in the Case Study section). To achieve the *dynamic* aspect in the process, a real-time schedule generation is in the future works. The goal of the ‘Real-time Feedback’ is to start a third-party simulation process to dynamically change the input information within the building energy simulation program. The

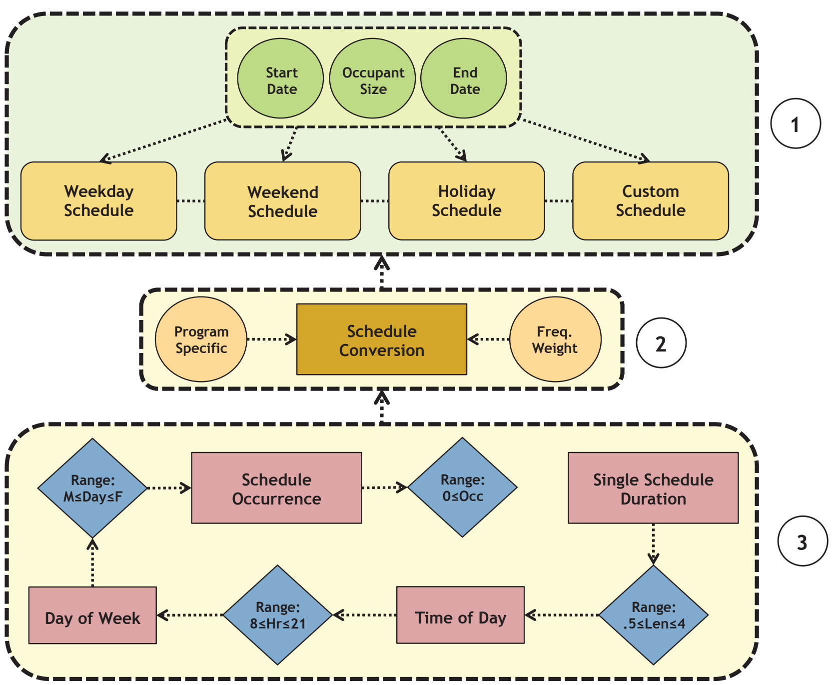


Figure 4.2 ‘Schedule Generation’ process for routine meetings (Lee et al., 2011)

need for this component is more evident when schedules other than occupancy and the demand for “what-if” scenarios increases – e.g., unexpected schedule changes, increased behavior in certain months, etc.

In order to further explain the ‘Dynamic Schedule’ (in particular, the ‘Schedule Generation’ process in Figure 4.1), one of the occupancy schedules – routine office meetings – was selected as a representative behavioral element (Figure 4.2). It primarily focuses on generating meeting schedules by way of a probabilistic process, as is commonly the case when making predictions of behavioral uncertainties [Malkawi et al., 2004][Sokolowski et al., 2009]. The following explains the process in depth (the methods explained here can be applied to all the collective schedules that may appear in ‘Schedule Generation’ in Figure 4.1):

- The simulation cycle consists of sub-cycles, e.g., ‘Weekday’, ‘Weekend’, ‘Holiday’, and one or more ‘Custom’ schedules (denoted as “1” on Figure 4.2), which is determined in advance as decisions on the simulation cycle and the occupant size are made by the user. This part is mostly done in the individual building energy simulation program.

- The meeting schedules are automatically generated by defining the four decision variables (rectangle symbols in “3” of Figure 4.2): 1) single meeting duration, 2) time of the day for a single meeting, 3) specific day of the week for a single meeting, and 4) number of meetings in a week. The statistical algorithm (diamond symbol in “3” of Figure 4.2) will follow a stochastic process to predict the probability of the decision variables.

- The ‘Schedule Conversion’ is the most important part of the process, helping to reconfigure the generated schedules into the language of the building energy simulation programs (denoted as “2” on Figure 4.2). This involves two sub-tasks. First, the data structure of the generated schedules needs to match the data structure of the simulation program of choice, hence, ‘Program Specific’. On that note, it would be convenient if the users work with an open-source simulation program (e.g., EnergyPlus) that enables users to customize the simulation process. Second, the conversion must take into consideration the difference in the magnitude of meeting *weights* (frequencies) for every single day – or ‘Frequency Weight’ (see below for details).

Applying the weights for different days has significant importance because the changes in the internal load (and energy consumption) due to schedules can vary depending on the specific time, e.g., from diurnal and seasonal effects. Moreover, the need to accommodate different sub-cycles defined in Figure 4.2 is resolved by generating individual schedules that reflect adequate weights – for example, more weight for weekdays than for holidays or weekends. In the end, the goal is to increase the simulation accuracy by emulating the real world schedule patterns.

The ‘Frequency Weight’ process calls for a *schedule prediction model* that generates these weights. However, trying to replicate the exact daily schedule is hardly possible, especially when an actual schedule history is not readily available. Therefore, the objective of the *schedule prediction model* will be to replicate the same mean value, the same spread from minimum to maximum, and the same number of days to mimic the actual schedules. The specifics of the schedule prediction model follow the methods suggested by Degelman [Malkawi et al., 2004]; with the input of mean frequency and standard deviation, the cumulative distribution function (CDF) of the simulated schedules (from “3” of Figure 4.2) will provide an acceptable estimation of the real schedules. Figure 4.3 is an example of the schedule prediction model for routine meetings in offices, or the CDF of daily operating schedule between 5am and 9pm. The x- axis is the time of the day, and y-axis shows the occupancy normalized based on an average daily occupancy of 0.38 (from the suggested office occupancy in ASHRAE Standard 90.1-2004, ranging from 0 to 1). The results are from a sample size of *n=100; m* indicates the average frequency of 1, 3, 6, 9 and 12 meetings per day. Although these numbers are deterministic, the results cover 95% of all probable occupancies (confidence interval level of ±0.8). In order to replicate future schedules, the *weight* will be the user inputs of mean frequency *m* and the standard deviation (δ) of the frequencies (refer to Degelman's methods for approximating the *δ).* The weights can be specified for a day, a week, or a month depending on the preferences of the user.

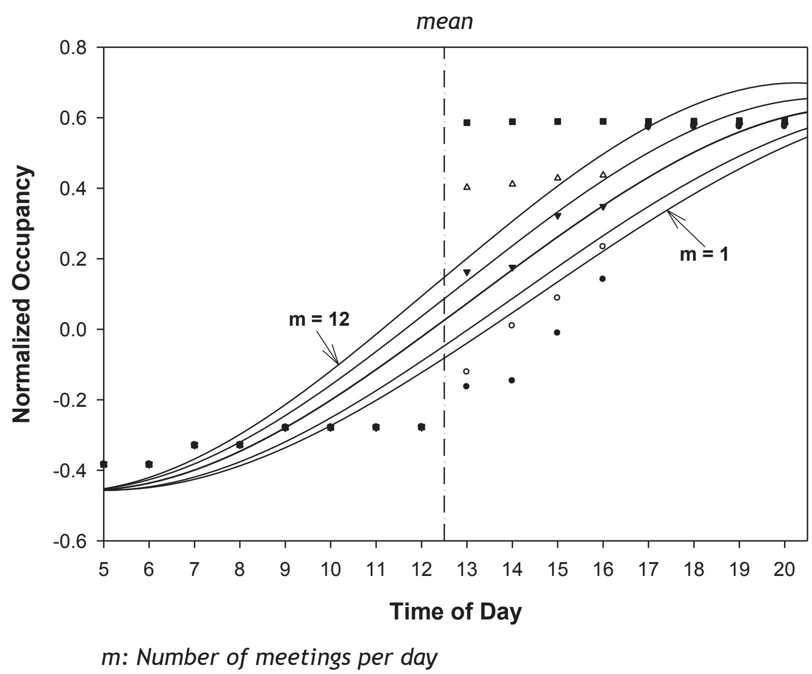


Figure 4.3 Schedule prediction model for routine meetings (Lee et al., 2011)

The next section covers a simulation case study that reflects the methods presented here. The study presents how the dynamic schedule can result in increased simulation accuracy for building energy consumption

4.1.3. Case Study

The case study is an execution of the 'Schedule Generation' process outlined in the previous 'Methodology' section (or dynamic schedule generation) using EnergyPlus. The case study is divided into two sections. The first section presents a description of the case study and an example run-through of the 'Schedule Generation' process. The next section discusses the simulation model and the results, comparing the actual and the simulated data.

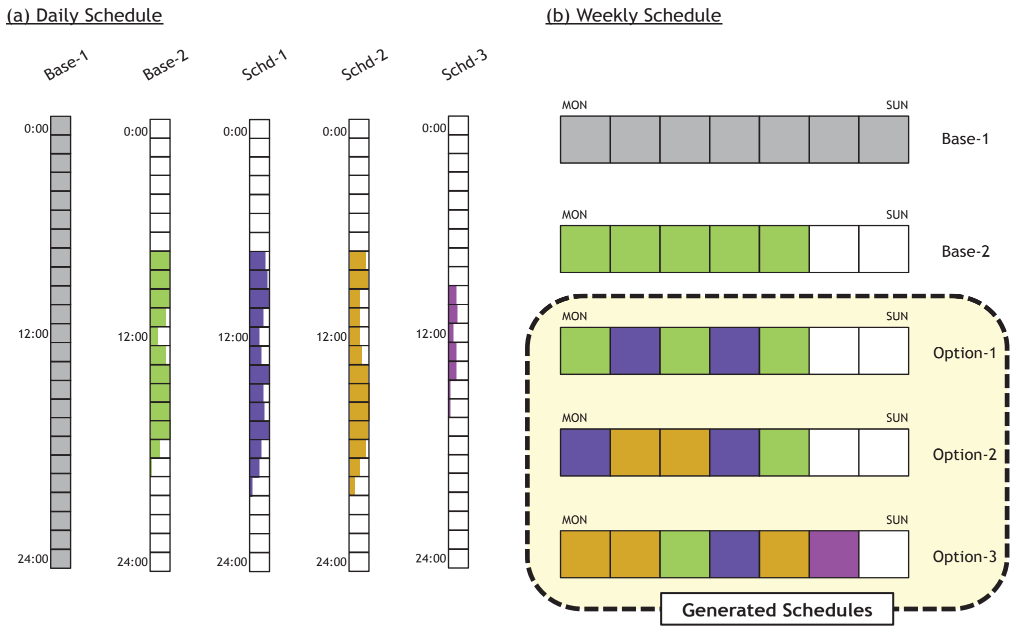


Figure 4.4 Daily and weekly schedule generated by the 'Schedule Generation' process (Lee et al., 2011)

(1) Description of the case study

Figure 4.4 is a representation that visualizes the outcome of the dynamic schedule generation in Figures 4.1 and 4.2. Figure 4.4-(a) presents five different daily schedules for occupancy. Each square block in the 'Daily Schedule' represents the fraction of occupancy in the given space, ranging from 0 to 1.

The 'Base-1' refers to the schedule used in the test suite Case CE100 as described in ANSI/ASHRAE Standard 140-2007. The 'Base-2' refers to that of a typical office space as described in ASHRAE Standard 90.1-2004. The first two schedules are for comparison purposes as they represent the most commonly used schedules adopted in simulation studies. The following schedules, 'Schd-1', 'Schd-2', and 'Schd-3', are selected samples generated by the process proposed in the experiment, reflecting the daily meeting patterns. Daily schedules are then converged into a 'Weekly Schedule' shown in Figure 4.4-(b). As mentioned earlier, the first two weekly schedules in Figure 4.4-(b) are deterministic with no intention of value changes in the simulation model: ‘Base-1’ and ‘Base-2’ are schedules constructed based on ANSI/ASHRAE Standard 140-2007 and ASHRAE Standard 90.1-2004, respectively. ‘Option-1’ to ‘Option-3’ (boxed in a dotted line) are the more realistic occupant schedules that reflect the weekly meeting patterns. Note that the accuracy of the predictions (or meeting occurrences) made by the dynamic schedule generation process depends solely on the statistical algorithm and the site-specific factors that are unique to individual buildings. This experiment does not define a robust algorithm, but will focus on establishing a foundation that would facilitate a gamut of algorithms later.

Figure 4.5 is a class diagram that delineates the process of dynamic schedule generation, its population, and the conversion into the building energy simulation program. This is intended for any programming language, so that the information generated from the previous step can be converted into the syntax/codes used by the building energy simulation program. As an object-based programming, the ‘Meeting Schedule’ model consists of the following class functions:

- Schedule Initialization: This part uses the *schedule prediction model* (Figure 4.3) to generate daily schedules that represent the meeting patterns (this will eventually expand to other occupant behaviors mentioned in the Methodology section).

- Default Settings: This is a predefined library of the baseline schedule, ‘No Work Day’ schedule, and the like that are part of the algorithm used in the previous ‘Schedule Initialization’ class. For example, the baseline for this particular case study is from the ASHRAE Standards, but options to customize or optimize it as needed are available.

- Schedule Allocation: This class allocates the generated dynamic schedules according to the characteristics of the simulation calendar (particular year the user is trying to simulate). For example, it will match the schedules for weekdays, weekends, holidays,

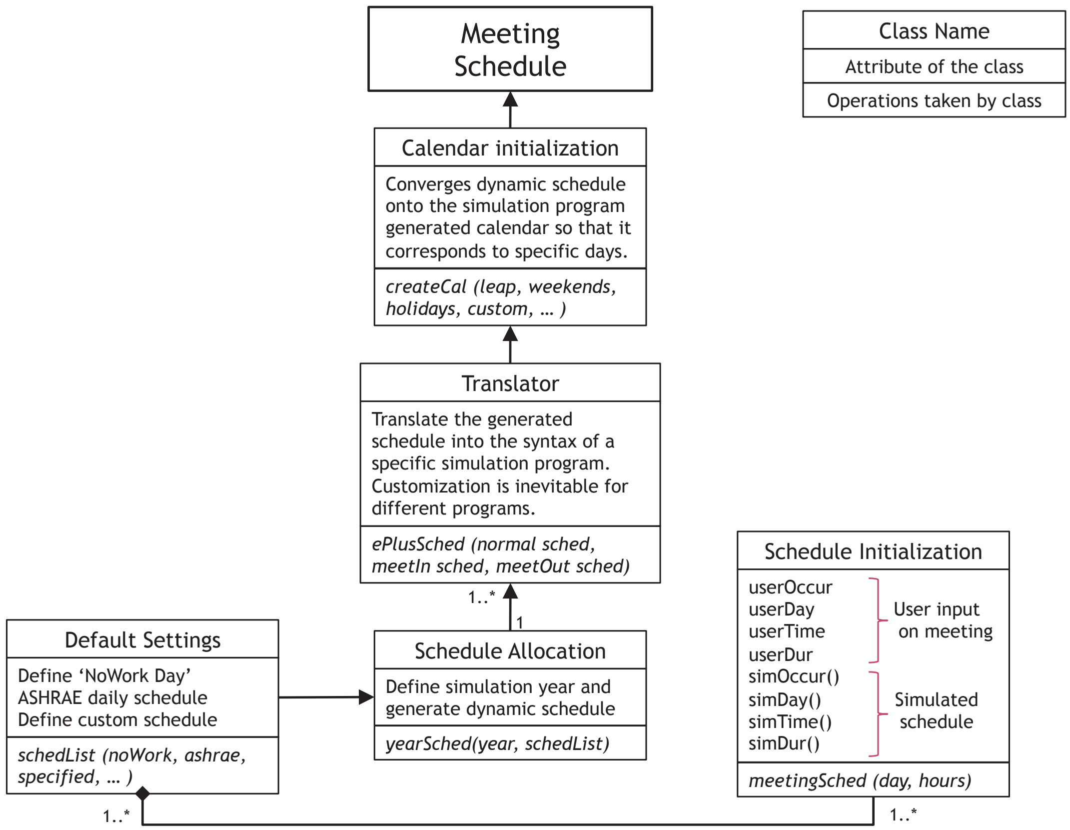


Figure 4.5 Class diagram for converting schedules for building energy simulation programs (Lee et al., 2011)

etc. The schedules populated are basically 0 to 1 occupancy for every hour of the day, stored in a CSV (comma-separated values) format.

- Translator: If all the class functions up to this point are generic, the 'Translator' class requires unique attention as different building energy simulation programs run on dissimilar program syntax. For example, in order to apply an alternative schedule in EnergyPlus, one needs to substitute an existing schedule, such as weekly, into three separate schedules: the schedule for the room with meetings, the schedule for the room where people vacate to attend the meeting, and the schedule for rest of the hours that is not affected by meetings.

- Calendar Initialization: This takes the schedules populated by the 'Translator' class and rewrites and/or reconfigures the building energy simulation program of choice to run on newly generated schedules.

(2) Simulation model and results

Based on this process, the schedule generated by the dynamic schedule generation process is compared to both the actual and ASHRAE schedules for validation. This study is conducted in EnergyPlus using a simulation model that includes a simple mechanical system, adopted from the CASE CE100 of ANSI/ASHRAE Standard 140-2007, which is a standard method for testing and evaluating EnergyPlus models [Henninger et al., 2010]. The basic test building is a rectangular $48m^2$ single zone (8m wide × 6m long × 2.7m high) office space with no interior partitions and windows. The building is a near-adiabatic cell with cooling load driven by user-specific internal gains. The mechanical system consists of a simple unitary vapor compression cooling system with air-cooled condenser and indoor evaporator coil, 100% convective air system, and no outside air or exhaust air. There is a non-proportional-type thermostat, heating is always off, and cooling is on if the zone air temperature is above 22.2°C. The simulation case runs for a three-month period, with results reported only for February. A constant outdoor dry-bulb temperature is set at 22°C.

Due to the limitations of the model, the simulation results fall short of representing the whole-building energy performance. Nevertheless, the model is sufficient for comparing different schedule settings, because it is sensitive to the changes of the internal load caused by the different schedules.

Figure 4.6 compares the energy consumption of HVAC with a conventional simulation schedule (as suggested in ASHRAE 90.1-2004), an actual schedule referenced from an existing building, and the dynamically generated schedule. The x-axis refers to three HVAC components that showed visible differences among the different schedules. The y-axis indicates the total energy consumption (in watts) for February. Note that while the actual schedule was manually constructed in EnergyPlus for each day of the week – a multiple input process – the *schedule prediction model* enables the user to mimic the actual schedule with a single input process (refer to *weight* in the Methodology section) without redundancy.

Figure 4.7-(a) describes the outcome of all the schedules (n=100, mean=4.8 meetings per day, *δ=0.396;* mean and *δ* from the actual schedule) generated for this case study, plotted as dots, using the 'Dynamic Schedule' method. The single line plot is the average of the generated schedules that was actually used in the simulation process (in accordance with the 'Initial Input', not 'Real-time Feedback', in Figure 4.1). Figure 4.7-(b) compares the occupancy for meetings of

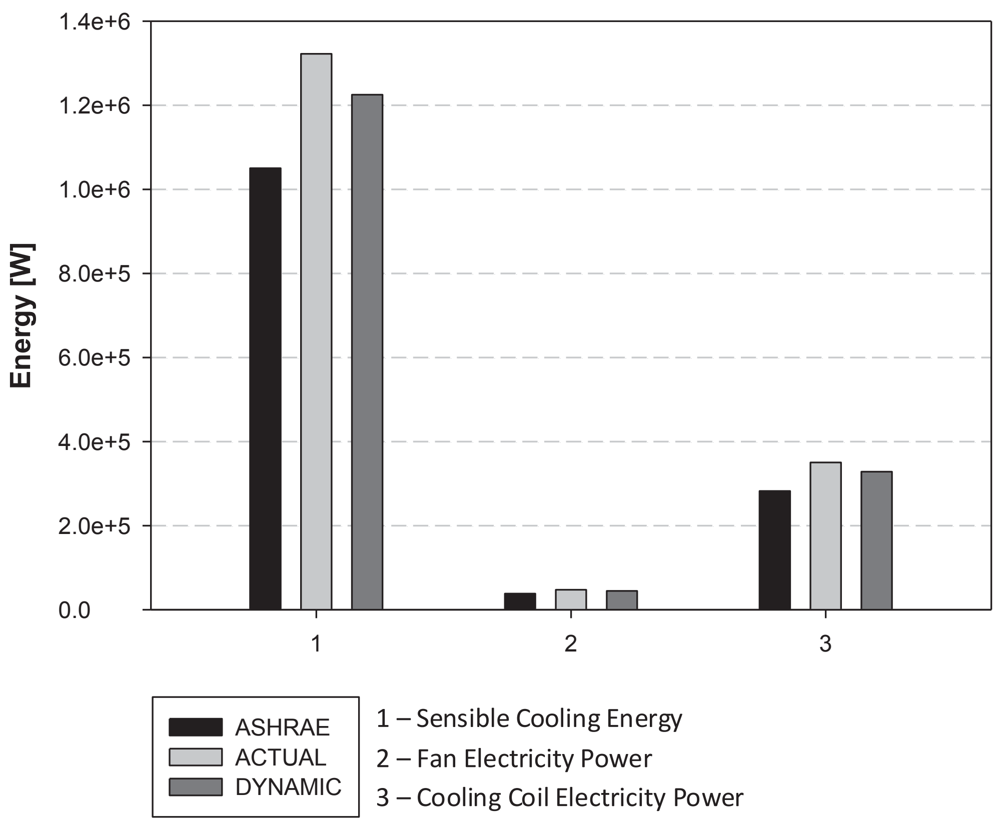


Figure 4.6 Simulation results comparison – ASHRAE, actual, and dynamic schedule (Lee et al., 2011)

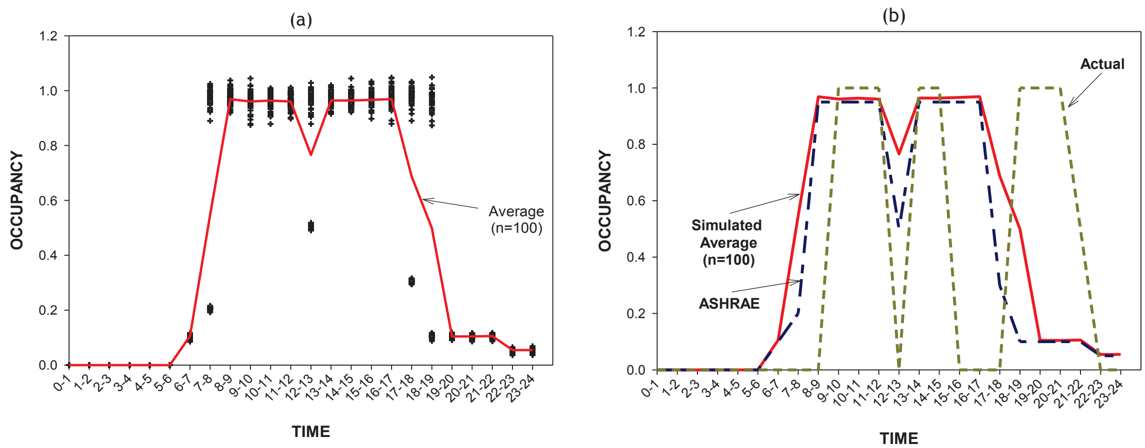


Figure 4.7 (a) Dynamically generated daily schedules, distribution and average (n=100), (b) Schedule comparison – ASHRAE, actual, and dynamic schedule (Lee et al., 2011)

the simulated, ASHRAE, and actual schedule used in the case study. The simulated schedule appears to resemble the ASHRAE schedule more than the actual schedule because the baseline for the *schedule prediction model* used in the case study was the ASHRAE schedule. In addition, the schedule patterns shown in Figure 4.7-(b) are not representative of all the schedules throughout the simulation cycle. Nevertheless, the EnergyPlus simulation results using the three schedules reveal that the resemblance between the simulated and actual schedules is noticeable; and in the end, the goal is increasing the prediction accuracy of the energy use, not obtaining the exact, unique schedule patterns.

The detailed simulation results and comparisons among the different schedules are summarized in Table 1. The first column of Table 4.1 refers to the x- axis described in Figure 4.7. Columns two to four list the total energy consumption, while the parentheses in the third and fourth columns depict the percent difference from the actual schedule simulation results. The last column delineates the percent increase in the accuracy of the dynamically generated schedule in comparison with the conventional ASHRAE schedule.

Table 4.1 EnergyPlus simulation results for the case study (Lee et al., 2011)

	Actual [kW]	ASHRAE [kW (Diff)]	Dynamic [kW (Diff)]	ASHRAE vs Dynamic
1	1322.2	1050 (-20.6%)	1225.2 (-7.34%)	16.7%
2	47.45	38.25 (-19.4%)	44.45 (-6.3%)	16.2%
3	350.26	282.35 (-19.4%)	328.08 (-6.3%)	16.2%

4.1.4. Results and Discussion

Based on the research process illustrated in Figures 4.1 and 4.2, the experiment conducted a simple simulation case study to find out how the building energy simulation program responds to the 'Dynamic Schedule' – both the methodology and literal sense of the dynamic meeting schedules. The results reveal that any changes in the schedule (and to the occupancy schedule in particular) are expected to cause noticeable changes in the overall energy consumption of the building. The 'Dynamic Schedule' process enables simulation users to simulate realistic occupancy and potentially other occupant behaviors that have an effect on the internal load and energy consumption. The resemblance between the actual and the simulated data is more evident with the energy calculation results than with the patterns of the schedules themselves. Moreover, the simulation results using the 'Dynamic Schedule' process showed up to 17% increased energy prediction accuracy compared to the industry's standard schedule, which commonly references the ASHRAE Standards.

Although the case study yielded a noticeable difference (17% increased prediction accuracy) over the current modeling approach (static), it used an oversimplified simulation model lacking robustness in mimicking true-life energy uses. As a next step, constructing a simulation model that accounts for realistic settings (exact weather data, complex geometry, etc.) is needed to optimize the 'Dynamic Schedule' process. In addition, to elaborate on findings more pertinent to human behavior research, other behavioral influences must be identified and incorporated into the ‘Dynamic Schedule’ process. Many occupant behaviors in buildings – such as control of light, windows, blinds, etc. – are predictable with the help of existing simulation capabilities. However, the ability to predict the behaviors that directly affect the fluctuation of an occupant’s microclimate (and thus influence the whole-building energy performance) is still lacking in recent studies. The experiment presents a theoretical framework and methodology that are constructed towards quantifying the impact of human behaviors (both frequency and magnitude of behavioral uncertainties) on the whole-building energy performance.

The causality between the dynamic schedule, occupant behaviors, and the overall energy performance is still in its infancy. Nevertheless, the preliminary simulation case study informs, to some extent, the behavior-energy relationship that will accredit our efforts to further pursue the research.

4.2. Single Behavior Simulation using ABM

A new methodology using agent-based modeling for human behavior simulation is presented. This approach aims to address the limitations and/or challenges encountered when dealing with behavioral components in existing building simulation programs. Also, it attempts to improve the behavior decision-making process by mimicking actual occupants in buildings. In a simulation experiment, a single occupant behavior was tested with agent-based modeling; results show that it demonstrated an ability to account for dynamic changes of the behavior, in real-time, along with the behavior impact on the microclimate and energy uses in a space. The intentions of the experiment were not just to illustrate a simulation methodology that could potentially better account for behavioral influences, but also to test to see if the ABM logic made sense. Therefore, the scope of the experiment was bounded so as to alleviate the complications that could affect the results, such as simulating a single agent and a single behavior that only relies on zone temperature values, dismissing the uncertainties of agent interaction, and minimizing the impact of mechanical systems (by having natural ventilation as the primary means for conditioning the supplied air).

4.2.1. Introduction

Human behavior in buildings has commonly been cited as a favorable attribute that explains the gap between the simulated and actual energy consumption data. Nevertheless, due to the uncertainties of behaviors, most current simulation research efforts neglect to fully account for realistic occupant behaviors [Zimmermann, 2006].

The objectives of this experiment are uncovering limitations in current practices for human behavior simulations and introducing agent-based modeling as a new methodology to address the limitations, so that real-life behaviors can be modeled.

The previous section has outlined the challenges of behavior simulation in buildings and explained how manipulating the simulation schedules (occupancy, lighting, equipment, and HVAC) can control the load changes due to occupant behaviors. In addition, an ongoing research on behavior simulation has identified the following limitations: First, a clear causality between behaviors and environmental stimulus is not fully defined and/or reflected in simulation programs. Typically, occupant behaviors such as window use or electric light use are either ON during operating hours, and OFF otherwise, without being responsive to the dynamic changes of the stimuli. Second, a single behavior decision is made for the entire space (or zone) based on an averaged environmental stimulus (such as temperature). For example, ASHRAE Adaptive Comfort Model prescribes the upper and lower temperature limits for the use of operable windows in a naturally ventilated space. The simulation takes the zone temperature average to determine one window use behavior for the entire zone. The limitations hardly allow us to describe realistic behaviors of an actual building; hence, they are likely to cause discrepant simulation results. To mitigate the shortcomings of current behavior simulation, an agent-based modeling approach is presented in the experiment.

In the following section, a simulation experiment is presented to highlight the potentials of agent-based modeling, and it discusses how agent-based modeling can be integrated into an existing building simulation program.

4.2.2. Methodology

Agent-based modeling (ABM), which consist of three core elements: (1) a set of agents, their attributes, and behaviors, (2) a set of agent relationship and methods of interaction, and (3) agents' environment, is used for simulating agent behaviors and agent interactions [Macal et al., 2010][Luck et al., 2003]. The scope and complexity of agent-based modeling depends on the specifics of the above three elements. Nevertheless, even the simplest agent-based modeling, which consists of agents and their relationship, could yield valuable findings about the system as a whole [Bonabeau, 2002].

The agent-based modeling presented in the experiment is programmed in Matlab, with a goal of having agents mimic building occupants by understanding the given environment (spatial and thermal), thinking about various behavior decisions in response to the environment, and executing behaviors. In order to make decisions, an agent is programmed to prioritize the level of its thermal comfort, and hence consider thermal parameters (e.g., temperature, humidity, air speed, etc.) as the main stimulus for behaviors.

Figure 4.8 illustrates how the use of ABM distinguishes itself from the existing method for simulating occupant behavior. The diagram compares the window use behavior in a naturally ventilated space. In an existing simulation program in Figure 4.8-(a), such as EnergyPlus, a fixed occupancy schedule, or "Human Occupancy," is what dictates the schedule for the window-use behavior, or "Ventilation Schedule." In addition, a "Predefined Behavior Input," such as equipment use, lighting use, or ventilation control mode (elaborated upon in the Experiment section), is decided on and used throughout the entire simulation cycle.

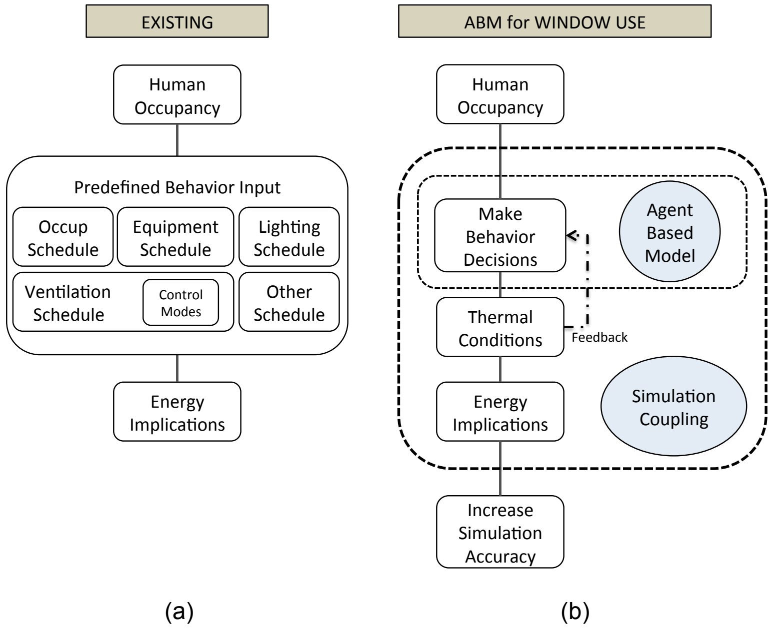


Figure 4.8 Comparison between existing and proposed simulation process

On the other hand, the proposed method in Figure 4.8-(b) uses the ABM to make decisions based solely on the comfort level of an agent (or occupant). After an agent makes a decision whether to open/close the window, the ABM sends the information to EnergyPlus to calculate the immediate changes in the thermal condition of the space and the energy implications. The communication is through an onion simulation coupling (using *MLE Legacy* and *BCVTB* elaborated in Section 3.4) so that the ABM and EnergyPlus can exchange information in real-time [Nghiem, 2012][Wetter, 2011]. The information consists of the thermal parameters that determine the comfort level of the agent, behavior decisions of the agent, and the behavior implications on thermal conditions and energy uses (exchanged at each simulation timestep).

The “Make Behavior Decisions” process is illustrated in Figure 4.8-(b), which basically covers the logic of the ABM and how the agent makes behavior decisions. The detailed background and theoretical framework related to the process are not covered in the experiment, while a brief summary is as follows:

- Observe: At each timestep, an agent observes the thermal parameters in the space to determine the level of comfort.
- Orient: An agent calculates a cost function to identify and rank different behavior options that would maintain comfort or mitigate discomfort in the space.
- Decide: Based on the thermal comfort model, an agent decides on the behaviors to consider and the magnitude of the behaviors. This is elaborated upon in the next section.
- Act: An agent notifies the execution of behaviors to all the ABM components to initiate the learning/training and agent interaction process. In addition, simulation coupling is conducted so as to calculate the changes in thermal conditions and energy uses.

4.2.3. Simulation Experiment

The experiment simulates the window-use behavior in a naturally ventilated space in EnergyPlus, coupled with the ABM approach. In a naturally ventilated space, the thermal conditions of the space are regulated primarily by occupants through opening and closing the windows [ASHRAE, 2004]. Therefore, the experiment only considers the zone mean air temperature as the stimulus for determining the window-use behavior. However, a more comprehensive ABM will calculate the Predicted Mean Vote (PMV) for thermal comfort to capture the effects of multiple behaviors.

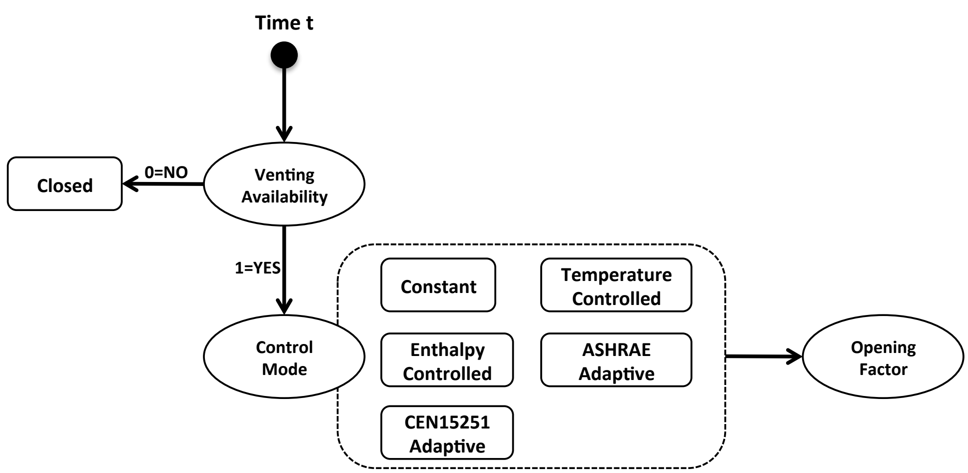
The experiment seeks not only to test the new ABM methodology, but also to quantify the impact of occupant behavior on building performance. Also, it compares how the results from the default EnergyPlus simulation differ from those that utilize the presented ABM, and attempts to seek opportunities to improve current simulation programs. Figure 4.9-(a) is a diagram of the simulation process embedded in EnergyPlus for window use behavior. There are two elements that determine the open/close decisions of windows in Figure 4.9-(a) – 'Venting Availability' and 'Control Model.' Venting availability is the hours of the day when natural ventilation is available, which typically matches the occupancy schedule in most EnergyPlus models. The different

'Control Mode' (also in Figure 4.8) implies how behavior decisions on window uses are calculated in EnergyPlus [DOE, 2011]. Those that are considered in the experiment are as follows:

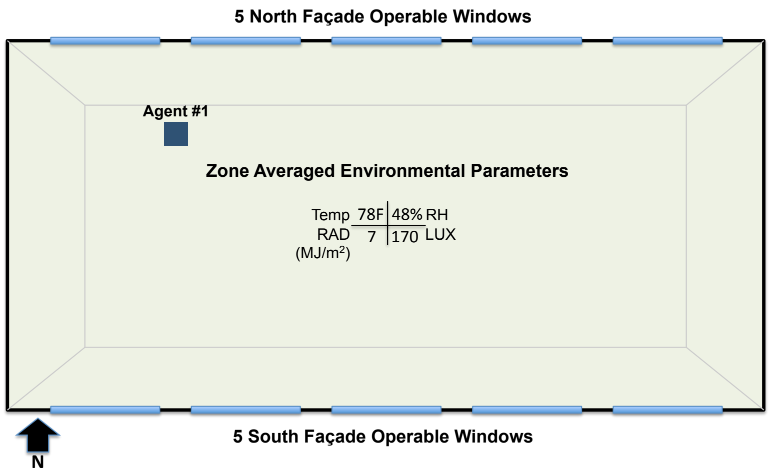
- Constant: All of the zone's operable windows and doors are open, independent of indoor or outdoor conditions.

- Temperature Driven: All of the zone's operable windows and doors are opened if $T_{zone} > T_{out}$ and $T_{zone} > T_{set}$ (T_{zone} = zone air temperature, T_{out} = outside air temperature, T_{set} = setpoint temperature).

- Adaptive thermal comfort: All of the zone's operable windows and doors are opened if the operative temperature is greater than the comfort temperature (central line) calculated from the ASHRAE Standard 55-2010 adaptive comfort model.



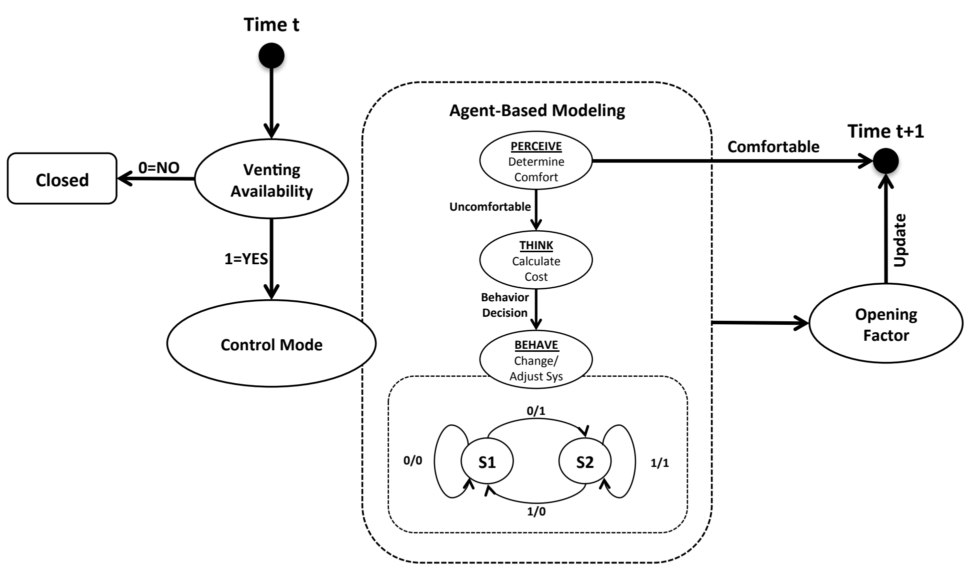
(a)



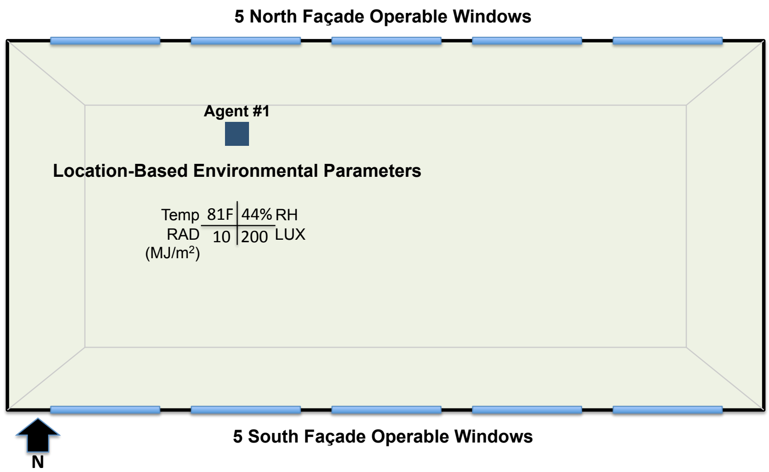
(b)

Figure 4.9 Window use behavior simulation process in EnergyPlus

The control modes for window use behavior, and most other behavior inputs in EnergyPlus, rely on zone-averaged environmental parameters, as illustrated in Figure 4.9-(b).



(a)



(b)

Figure 4.10 Window use behavior simulation process in ABM

Figure 4.10-(a) explains how the ABM is coupled with EnergyPlus, which can be compared with the process shown in Figure 4.9. Instead of the embedded control mode provided by EnergyPlus, the ABM conducts an onion coupling; at each timestep it will perceive the level of occupant comfort satisfaction and determine whether to open/close the window (refer to the Methodology section). First, an agent perceives the environment as it observes the zone air temperature that is related to its immediate surrounding (as in Figure 4.10-(b)[6]), which is information transferred from EnergyPlus to ABM through simulation coupling (Section 3.4). If an agent is comfortable (based on the adaptive comfort model), there is no window-use behavior, but otherwise, an agent will think about its options to respond to the comfort dissatisfaction – or 'Calculate Cost.' In this case, only a single agent and a single window-use behavior are considered. Hence, the cost primarily calculates the sum of an agent's belief on the effectiveness of window use for comfort and the ability to actually control the windows [Fishbein et al, 2010], without consideration for agent interactions. If the cost exceeds a certain criteria, behavior is executed (Section 3.3.3).

[6] Due to the absence of current simulation capabilities to calculate the proposed location-based parameters, the experiment had to use the zone-averaged parameters. This is addressed in the Conclusion section.

‘S1’ and ‘S2’ in Figure 4.10-(a) refer to the two states of the behavior, closed and opened, respectively. The four arrows between the two states refer to the four transitions: closed to open, opened to close, remain opened, or remains closed. This information is exchanged from the ABM to EnergyPlus to not only calculate the impact on energy uses, but also the microclimate of the space that would affect decision-making process at the next timestep (‘Time t+1’).

Figure 4.9-(b) and Figure 4.10-(b) represent the space used to simulate window-use behavior in the experiment. The simulation settings are as follows:

- Simulators: EnergyPlus version 7.01 and Matlab.
- Weather: Philadelphia, PA, USA.
- Gross floor area: 669.3 m^2 (Single zone).
- Program: Generic office area.
- Window to Wall: 30% (5 windows at North and South façade).
- Hours simulated: 8760 hours.
- Number of agents: a single agent.
- Mechanical: Fan-coil unit.
- Ventilation: Mixed-mode ventilation.

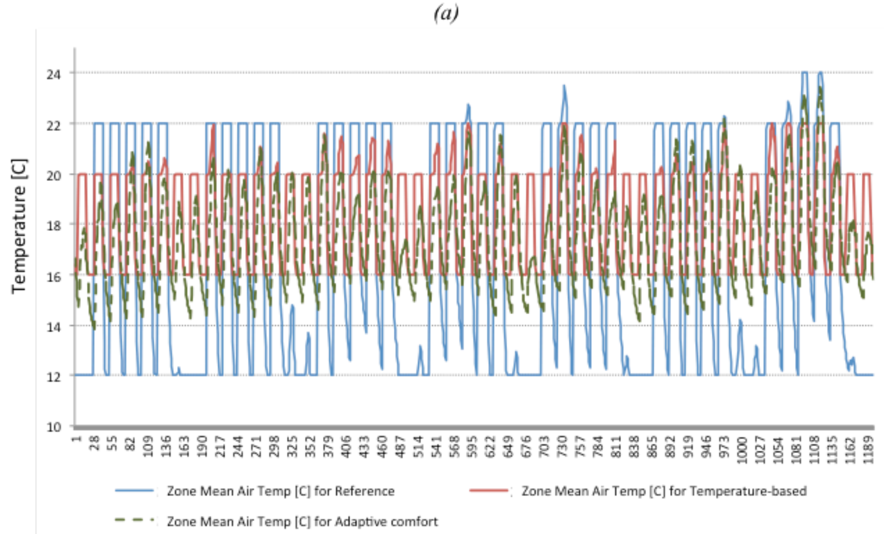
The simulated space is conditioned with a fan coil unit, with mixed-mode ventilation (alternate) allowed during the simulation period.

4.2.4. Results and Discussion

Figure 4.11-(a) is a graph showing temperature trends populated by the ABM, from January to March (first 1200 hours) of the site. It compares the zone mean air temperatures dictated by three

control modes for window use behavior: *Reference* case with no window use behavior (existing EnergyPlus default settings), *temperature-based* control mode (using an existing EnergyPlus algorithm), and *adaptive comfort* control mode. One of the most noticeable observations is that allowing control to adjust the windows resulted in decreased diurnal temperature swings. This is consistent throughout rest of the colder months (November to December). Even between the two

(a)



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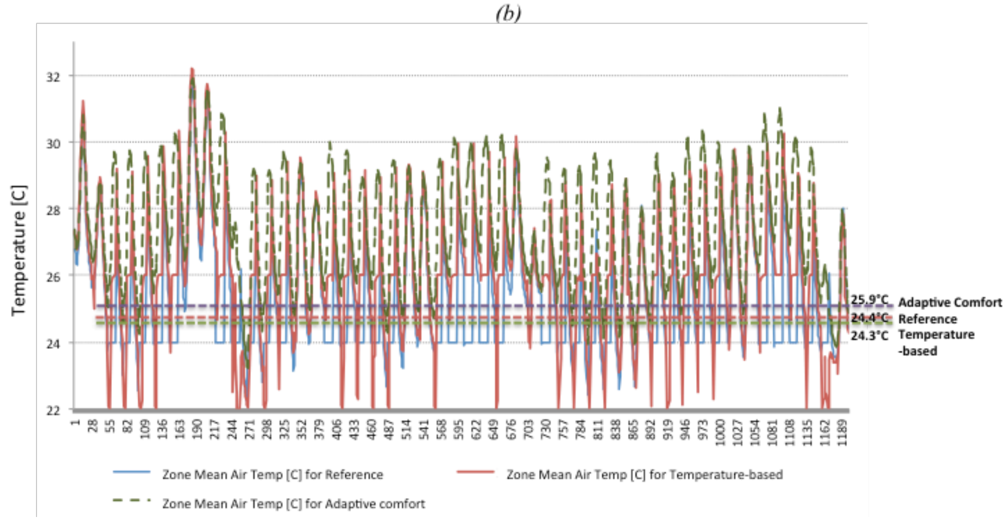


Figure 4.11 Zone mean air temperature trend comparison for different behavior control modes, (a) January to March, (b) July to September

control modes for window uses (temperature and comfort), comfort-based adaptive comfort control mode seems to have smaller fluctuations. As for the hotter months from July to September, as in Figure 4.11-(b), all the temperature trends seem to parallel each other. The average zone air temperatures for the reference case, temperature-based control mode, and adaptive comfort control mode are 24.4°C, 24.3°C, and 25.9°C. This indicates that comfort-based behavior decisions result in larger zone air temperature, and ultimately incur higher internal heat gain in the space. The results may imply that having some control over building systems to manipulate the built environment may increase the tolerance for operative temperature, which resembles the adaptive model for thermal comfort [de Dear et al., 1998]. In terms of the annual heating and cooling demand, allowing the window use behavior resulted in higher overall demands. As shown in Figure 4.12, the temperature-based control for window use resulted in the highest annual heating (35.4kW/m^2), and the adaptive comfort mode in annual cooling demand (46.4kW/m^2).

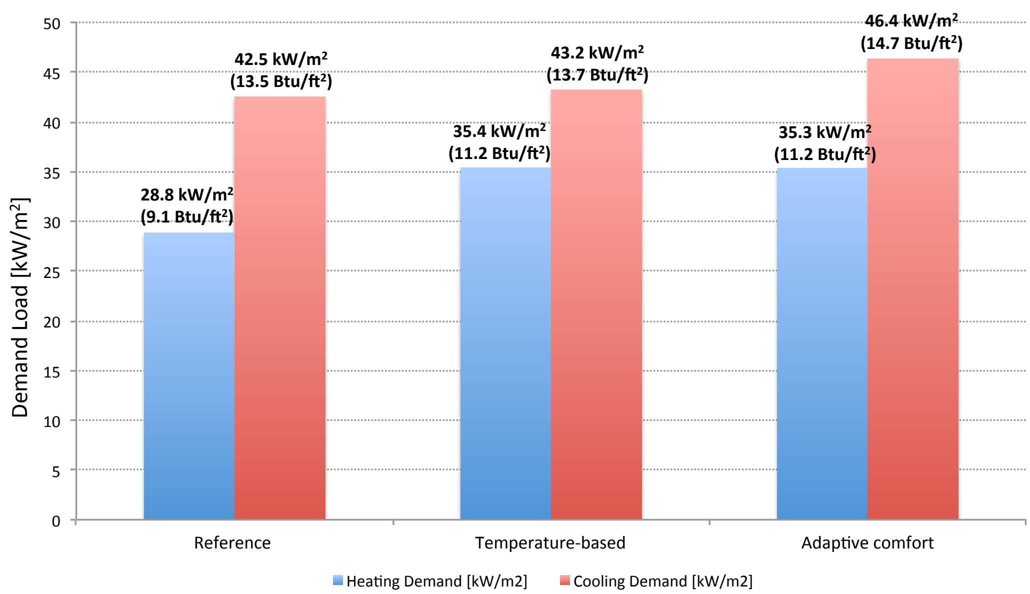


Figure 4.12 Annual heat and cooling demands for different window use behavior control modes

The two results make it clear that even accounting for a single behavior could result in dissimilar simulation results compared to the reference mode.

The experiment also compared the window-use behavior in the two simulation platforms. Given the same simulation settings, a window-use behavior based on temperature-based control mode was simulated in the default EnergyPlus model and the ABM coupled EnergyPlus model. Figure 4.13 is the sum of total temperature difference in the zone mean air temperature between the two simulation methods. The results illustrate how the ABM approach creates different thermal conditions in the space from a non-ABM approach, despite using the same calculation algorithm. The difference is more evident during the hotter months of the year – up to almost 12°C hourly.

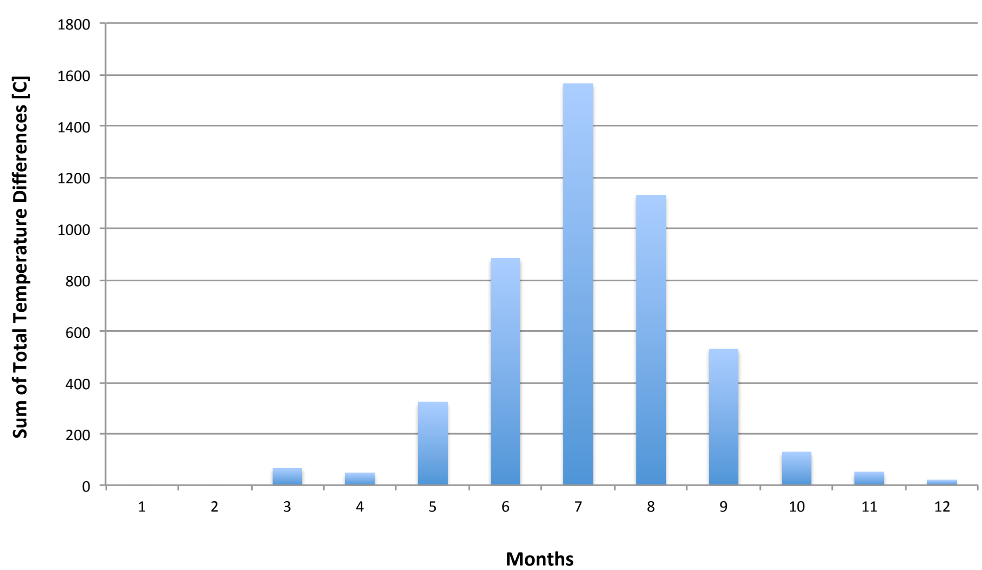


Figure 4.13 Zone mean air temperature differences (monthly sum) as a result of window use behavior based on temperature-based control mode, between existing and ABM simulation results

Responding to the limitations of current simulation practices that oversimplify human behaviors, the experiment presented a new simulation methodology that couples an existing energy simulation program with agent-based modeling. The main intention of agent-based modeling (ABM) is to closely mimic the behavior of an actual occupant from an occupant perspective, rather than relying on external forces such as occupancy schedule, which are not always representative of the entire occupant population.

The experiment using ABM was compared to the existing simulation process, investigating window use behavior in a naturally ventilated space. ABM was able to capture the behavioral impact on energy consumption, and also dynamically update the thermal conditions of a space. That is, while the existing simulation programs were only concerned with a behavior-energy causality, the ABM was sensitive to the subtle effects of the behavior on occupants' thermal conditions in real-time, which implies that some behavior events are dependent both on the environmental stimuli and on other behaviors.

The energy results were not as intuitive as expected. The increase of window-use behavior (for natural ventilation) should have lowered the overall energy consumption due to the lessened use of mechanically conditioned air. The results indicate that adaptive comfort control mode for window-use behavior yields the highest end use energy demand, which suggests with the following possibilities:

- Maintaining the level of comfort in a space incurs other emerging energy demand, e.g., a ventilation heat loss due to opening the windows.
- The logic used in the ABM was not robust enough to fully account for the expected energy savings.
- Overall increased zone air temperature, for the comfort-based ventilation control, was compensated by other mechanical entities to meet the HVAC setpoints.

Overall, the assumed advantages of ABM are the following:

- Instead of using zone-averaged thermal parameters, the ABM tries to use those that directly affect an agent in real-time.
- Therefore, multiple agents can incur varied behavior decisions in a zone, and truly realize the ABM mindset – describing a system from the perspective of its constituent units [Bonabeau, 2002].
- Ultimately, the ABM allows a simulation process to closely emulate the real world, helping to increase simulation accuracy by increasing the prediction accuracy of internal heat gains that result from occupant behaviors.

The experiment was successful in demonstrating the validity of the ABM approach in simulating occupant behavior. First, it reinforced the hypothesis of the dissertation that behavior impact on the thermal conditions of the space was significant. Second, it was capable of accounting for the dynamic behavioral changes within the space. Finally, the energy use calculations yielded comparable results, which imply that the methodology was robust enough for this simple simulation exercise. The next experiment is to incorporate other behaviors, such as blind-use behavior, personal cooling/heating equipment, adjusting clothing level, etc. By optimizing the ABM logic, the expectation is to have a holistic understanding of occupant behaviors in buildings, and ultimately to use the knowledge to increase the prediction accuracy of building simulation programs.

4.3. Multiple Behavior Simulation using ABM

This experiment uses agent-based modeling to simulate multiple occupant behaviors in an operating commercial building. The results of a single behavior simulation in the previous section reveal that the ABM approach was comparable to EnergyPlus in terms of the overall energy consumption calculations, which suggests that the new methodology is suitable for the simplest simulation run. As the scope of the dissertation does not cover validation of the model through case studies or actual measured data, the experiments assume that the ABM logic is ‘good enough’ to pursue further investigation. The purpose of the agent-based modeling is to use an autonomous agent that interacts with both its environment and other agents to mimic a real-world occupant that makes behavior decisions based on the level of its thermal comfort. Individual agent behaviors are simulated, and then the results are aggregated to explain the behavioral phenomena of the building as a whole. Using simulation coupling, the behavior impact on thermal conditions and energy use can be scrutinized. The experiment was conducted to see how an agent considers five behaviors (clothing level, activity level, window use, blind use, and space heater/personal fan use behaviors) to achieve its comfort goal, and how an agent adapts to the dynamic thermal changes in the space to maximize both comfort and energy savings.

4.3.1. Introduction

In an effort to increase the prediction accuracy of building energy simulation programs, modeling building occupant behavior and its impact on energy use has gained an increasing attention in recent simulation research. Typically, simulation results underestimate the building energy consumption compared to the actual measured data, with discrepancies up to 30% or more [Yudelson, 2010]. This dissertation has held occupant behaviors liable for the discrepancy as behaviors are constantly observed in the workplace to mitigate the thermal microclimate, in order to maintain (or increase) the level of occupant comfort [Baker et al., 2000]. Hence, it is important to have a good prediction of the behaviors, along with how they impact the overall building energy performance.

4.3.2. Agent-Based Modeling Overview

The ABM in the experiment is primarily responsible for making behavior decisions and linking building energy simulator (via simulation coupling) to calculate energy use and changing thermal conditions as a result of the behaviors, as shown in Figure 3.13. Agent characteristics are described in Section 2.1.1, Appendices C and D. A class diagram of the actual Matlab codes is illustrated in Appendix F.

4.3.3. Methodology

4.3.3.1. Human Behavior Model

Human behavior model encompasses the three processes that are essential in initiating the behavior research: define behaviors, identify behavior triggers, and measure and quantify behaviors. The ABM in the experiment is focused on behaviors that affect the occupant thermal comfort (which typically ranks as the highest identified source of occupant dissatisfaction in a leading post-occupancy comfort survey [CBE, 2010]) such as window use, blind use, and space heater or personal fan use. The behaviors are not only closely related to thermal comfort, but are part of the building system with implications on building energy use once changes in the behaviors are implemented. Behaviors are dictated by thermal comfort, and are closely correlated with a specific environmental parameter (usually climate data) or behavior triggers. It is important to understand the trigger mechanism for occupant behaviors because there needs to be a

Table 4.2 List of behaviors and relevant PMV parameter (behavior trigger)

Behaviors	PMV Parameter (Behavior trigger)	Initial Values	Control Values
Occupant activity level	*met* value	Seated (met=1.2)	Min met=1.0 Max met=2.0 Increment=0.1
Blind use	Radiant temperature	Close	Open/Close
Clothing level	*clo* value	Winter clo=1.0 (Light business suit) Summer clo=0.6 Shoulder clo=0.6 (Trousers and shirt)	Winter: Min clo=0.8 Max clo=1.0 Increment=0.2 Summer/Shoulder: Min clo=0.5 Max clo=0.7 Increment=0.1
Door use	Air speed	Close	Open/Close
Fan/heater use	Air temperature	Off	On/Off Fan speed=0.45~0.65m/s
Window use	Air speed (m/s)	Close	Open/Close Air speed from natural ventilation=0.4~0.6m/s

quantitative metric to represent incremental behavior changes and to assess the occupant comfort level. On that note, the experiment determines the comfort level by adopting Fanger's PMV model [Fanger et al, 2002]. Table 4.2 is an example of a behavior list and its connection to the trigger mechanism (also PMV parameter). Also, the table lists the initial behavior values associated with specific behaviors/PMV parameters that are used in the experiment. The control values in Table 4.2 refer to the range of the behavior values applied, such as minimum, maximum, and other increment changes incurred from behaviors (refer to Appendix D for details).

As an essential process in making behavior predictions, the tactic for measuring and quantifying occupant behaviors is rooted in the idea that 'human behavior follows reasonably and often spontaneously from the information or beliefs people possess about the behavior under consideration' [Fishbein et al., 2010], which is elaborated in Section 3.2. Based on this assumption, the beliefs associated with occupant behaviors can be categorized as the following (adopted from the Reasoned Action Model): behavioral beliefs, control beliefs, and normative beliefs [Fishbein et al., 2010].

4.3.3.2. Cost Function

Calculating the cost for the agent follows the cost function introduced in Section 3.3.3, which is used to help an agent in the ABM to make decisions on 'what' and 'how many' behaviors to execute. To accommodate the scope of the experiment, the following assumptions were made in applying the cost function. First, an agent assumes equal behavioral beliefs toward all the behaviors with opportunities to update them throughout the simulation cycle. Second, an agent tests the effectiveness of a particular behavior by allocating higher control belief value to the behavior. Third, the single agent in the experiment assumes equal normative beliefs toward all behaviors without belief updates. Finally, the weight coefficients for all behavior beliefs are assumed to be equal (refer to Section 3.3.3 for details).

Table 4.3 is a list of behavior belief values used in the cost function for the experiment. Each behavior starts with initial behavior belief values (behavioral, control, and normative from a range between 0 and 1), but is subject to change throughout the simulation cycle – i.e., an agent evaluates the effectiveness of each behavior and updates the behavior beliefs accordingly. In general, agents in the ABM actively update behavioral beliefs, while users manipulate the control beliefs to distinguish the effectiveness of a specific behavior – for example, to emphasize the role of two behaviors as shown in column four of Table 4.3. In line with the assumptions made to simplify the experiment, all normative beliefs and weight coefficients are equal.

The behavior belief values in Table 4.3 are used to calculate the cost, or the overall belief towards individual behavior in achieving its goal, which an agent uses during its decision-making process (refer to Section 3.3.3).

Table 4.3 List of behaviors and belief values

Behavior Beliefs		Initial Values	Prioritize Behavior #1 and #5	Belief Updates	Weight Coefficients
Behavioral	Behavior #1	0.5	0.5	Yes (At each timestep)	1.0
	Behavior #2	0.5	0.5		
	Behavior #3	0.5	0.5		
	Behavior #4	0.5	0.5		
	Behavior #5	0.5	0.5		
Control	Behavior #1	0.4	**0.5**	Yes (User controlled)	
	Behavior #2	0.4	0.4		
	Behavior #3	0.4	0.4		
	Behavior #4	0.4	0.4		
	Behavior #5	0.4	**0.5**		
Normative	Behavior #1	0.5	0.5	No (Fixed)	
	Behavior #2	0.5	0.5		
	Behavior #3	0.5	0.5		
	Behavior #4	0.5	0.5		
	Behavior #5	0.5	0.5		

(Behaviors: #1-clothing, #2-activity, #3-window, #4-fan/heater, #5-blinds)

4.3.3.3. Make Behavior Decisions

Making behavior decisions is the most important component in the experiment and epitomizes the main ABM function. A detailed state-transition diagram is presented in Figure 4.14 (a detailed expansion of the ABM process illustrated in Figure 3.13), which illustrates how the ABM makes

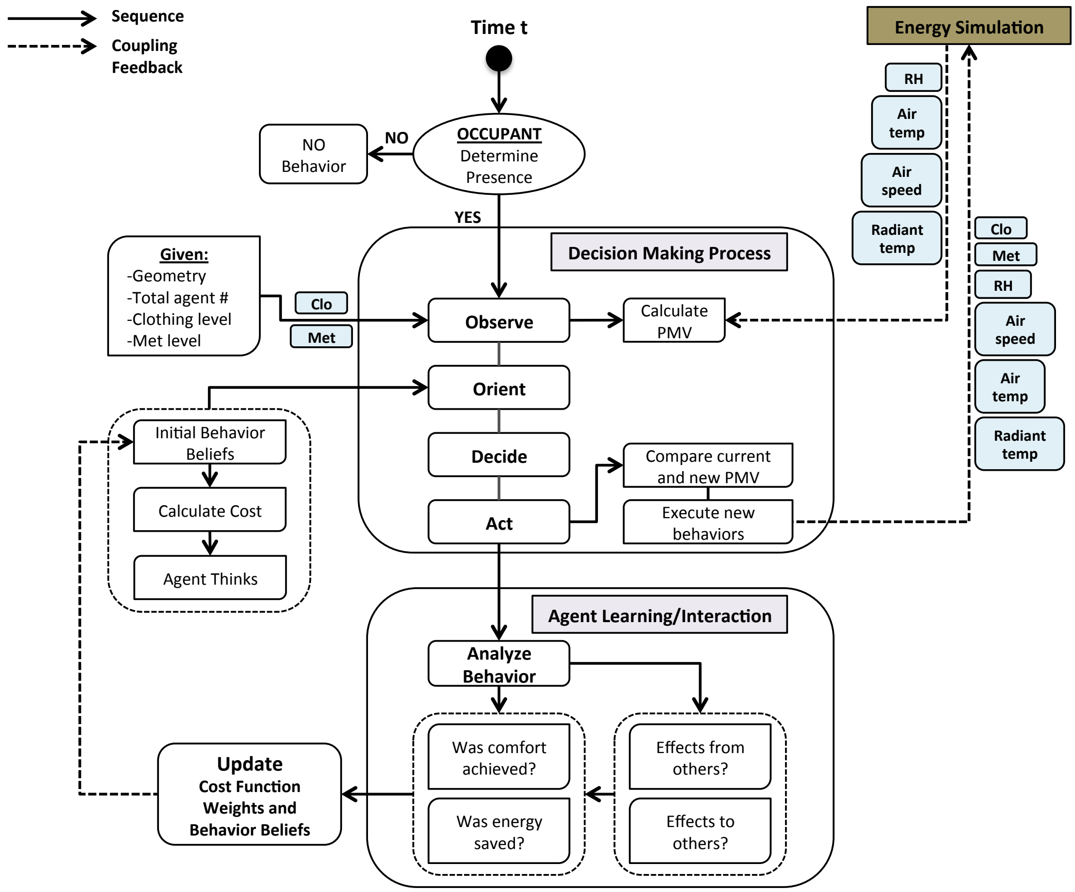


Figure 4.14 Main ABM function (decision-making process and simulation coupling)

behavior decisions and communicates those to outside building energy simulator at each timestep. At time *t*, if an agent is occupying a space, it goes through the following procedures to make behavior decisions.

1) Decision-making process

The ABM in the experiment is intended to be an open architecture program with user-defined input values, including the building geometry, the initial clothing levels for major seasons, and the initial activity level in the workspace. An agent first observes its surroundings, which is defined by the user input values and the thermal conditions of the space (Appendix C and D). The thermal conditions are analogous to those environmental parameters that allow an agent to calculate its PMV in order to keep track of the comfort level. An outside simulator provides the environmental parameters to an agent through simulation coupling (Section 3.4). An agent orients itself by following three steps. First, an agent is populated with initial behavior beliefs (in Section 4.3.3.1), which can either be user-defined (if survey results from target audience is available) or randomly distributed. Second, a cost function is calculated to determine the cost of each behavior. Third and finally, an agent thinks and ranks the behaviors in order to figure out which ones are most effective in achieving its comfort goal. Depending on the level of dissatisfaction on comfort, the number of behaviors to consider may vary as well. An agent decides on a set of behaviors to execute as a means to maintain or increase its comfort level. This decision implies not only the type and number of behaviors to execute, but also the increment changes from the previous state. Lastly, an agent acts by sending the behavior changes to the outside simulator to calculate real-time thermal changes and energy use.

2) Agent learning/Interaction

After executing behaviors, an agent evaluates their positive/negative influence on comfort (or other agent goals). As part of the learning function, an agent keeps track of the executed behaviors in its memory, comparing them with their efficacy in achieving the agent's goals. From the comparison, an agent upgrades the behavioral belief for each behavior. For example, assume behavior #1 was evaluated, where the initial behavioral belief of 0.5 could be upgraded to 0.6 when it was very effective, 0.55 when marginally effective, and 0.4 when very ineffective in improving the comfort level. A detailed explanation is provided in Section 3.3.4.

Agent interaction is an important characteristic of a multi-agent ABM, which is controlled by the normative belief that determines the degree of impact an agent behavior will have on other agents, and vice versa. Initial values for the normative belief are case specific, and require some form of a survey prior to the simulation experiment [Fishbein et al., 2010]. However, due to the absence of such survey data, one can only assume the influence of agent interaction is muted, so as to avoid the added uncertainty inherent in the ABM approach.

4.3.3.4. Simulation Coupling

Along with the decision-making process, the capability to communicate with outside simulators (simulation coupling) is an essential ABM function. Simulation coupling is an application in which at least two simulators – each solving an initial-value differential or difference equation – are coupled to exchange data that depend on state variables [Wetter, 2010]. Once an agent behavior is observed, the ABM uses an outside simulator to calculate the changes in the environmental parameters, agent comfort level, and (ultimately) the energy use pattern. The changes are tracked every hour (or per the specific timestep used in the simulation experiment) and reflected in the next hour by updating agent and building system properties (refer to Section 3.4 and Appendix E for details).

4.3.4. Experiment and Simulation Results

In section 4.2, simulation results have shown that a single window use behavior using ABM resulted in slightly higher energy consumption (2% EUI and 8% cooling demand) compared to an existing simulation result using EnergyPlus default inputs. Along the with energy use, the comparison also revealed that the thermal conditions were quite different – the sum of total zone mean air temperature differences between the two cases reached up to 12°C hourly (especially in the summer months). This section introduces a more comprehensive experiment that applies the ABM methodology in simulating multiple behaviors. The experiment was conducted with a premise that the ABM approach does yield different trends in both the thermal conditions and energy use in a space. The goal of the experiment is to investigate how different behaviors impact the whole-building energy use and occupant comfort.

4.3.4.1. *Experiment Settings*

The geometry and simulation settings that pertain to the EnergyPlus model are identical to the previous section. The experiment is observing one agent situated in a single-zone office environment (669.3m^2) in Philadelphia (PA, USA), with 30% window-to-wall ratio, predominantly fan-coil mechanical system with mixed-mode capabilities, and simulated hourly for one year (8760 hrs).

As an open-architecture program, the ABM in the experiment allows for various user-defined inputs to be used in order to accommodate the user's different needs, and to easily calibrate or validate the results. A full list of these inputs is found in Figure C.1 in the appendix, while the following summarizes those that are applied to the experiment:

- Behaviors tested: adjusting clothing level, adjusting activity level, window use, blind use, space heater use, and personal fan use.
- Behavioral belief: Same initial value 0.5 assumed for all behaviors.
- Control belief: Same initial value 0.4 assumed for all behaviors.
- Normative belief: Same initial value 0.5 assumed for all behaviors.
- Belief coefficients: Assumed to be equal (=1).
- Initial 'clo' value: Winter=3, summer=2, spring/fall=2 (refer to Table C.1)
- Initial 'met' value: All seasons=3 (refer to Table C.2).
- Space heater: 1000 Watts/person.
- Personal fan: 500 Watts/person with 0.45-0.64 m/s fan induced air speed [DOE, 2011].
- Natural ventilation: Produces 0.4-0.6 m/s air speed [ISO, 1993].

- Blind type: Interior blinds, horizontal slat angle, and temperature-controlled.

4.3.4.2. ABM Output

The ABM produces visual representations of the results to capture meaningful findings, or emergent phenomena, about building operations. First, hourly behavior trends, or the actual behavior parameters (such as the *clo* value, *met* value, and others) are plotted. In addition, a total number of hours when a behavior has been executed is accounted for and plotted monthly (Figure 4.15). These two plots help to identify the specific time of the year when a particular behavior occurs more or less that other times (hereinafter, referred to as ‘behavior trend graphs’). Secondly, a yearly PMV value for the agent(s) is plotted to understand how effective the agent behaviors are in achieving the agent comfort goal. Finally, a series of correlation studies are conducted: PMV vs. cost function, PMV vs. behaviors, and PMV vs. behavioral beliefs (using Pearson’s correlation). The purpose of the correlation study is to not only understand the effectiveness of a behavior towards comfort, but also to provide an insight on ABM calibration by applying more weights to behaviors that yield stronger correlation. All energy related results are created in the EnergyPlus output folder.

4.3.4.3. Case Study #1 –Behavior priority

Typically, most occupants have a clear idea of which behaviors are more accessible than others – for example, a centrally controlled thermostat, non-operable windows, automated blinds, and others that inherently prohibit or discourage certain occupant behaviors. The information on the accessibility of behaviors would define the control beliefs in the ABM. Without such information in hand, one could use the ABM to test the effectiveness (or emphasize the role) of a specific behavior by allocating a higher control belief value. For example, if the goal is to see the effectiveness of a window use behavior, its initial control belief can start with 0.5 instead of 0.4. Likewise, a set of experiments can be conducted assigning priority to the six different behaviors (fan and heater use was consolidated as equipment use). As a result, individual behavior was scrutinized for its contribution to both the comfort and energy savings.

Table 4.4 Analyses on behavior priority

Behavior	EUI ($kBtu/ft^2$)	Time Not Comfortable Based on Simple ASHRAE 55-2004	% of Hours Comfortable	Behavior vs Comfort Correlation (Pearson)					
				Clo	Met	Window	Fan	Heater	Blinds
Blinds	59.15	2753	68.6%	-0.458	-0.501	-0.058	0	-0.256	-0.636
Clo	59.33	2740	68.7%	-0.435	-0.5	-0.02	0	-0.524	-0.643
Fan/Heater	**59.13**	2751	68.6%	-0.399	-0.49	-0.123	0	-0.295	-0.633
Met	59.83	**2725**	**68.9%**	-0.449	-0.522	-0.208	0.122	-0.422	-0.667
Window	59.95	2737	68.8%	-0.477	-0.54	-0.216	0.148	-0.426	-0.644

Table 4.4 is a summary of five experiment cases where the role of a single behavior (first column) is emphasized by assigning it the highest control belief value (0.5), while the rest of the behavior beliefs were equal (0.4). The second column indicates the energy use intensity (EUI) to see the different effects of behaviors on energy use. The third and fourth columns are related to agent comfort level. The criterion for determining comfort is based on the ASHRAE comfort model that is part of the EnergyPlus calculations. The rest of the table looks at how rest of the behaviors correlate to the agent comfort when one behavior was teased out and given a priority for accessibility. According to Table 4.4, the agent was most comfortable by changing the activity level in a space (met value), while consuming less energy by using personal fan or space heater to maintain its comfort. Prioritizing the use of external equipment would incur added energy use, which seems to make the above result counterintuitive. However, the correlations reveal that the significance of space heater and fan use (-0.295 and 0, respectively) was relatively low, which means that the overall execution of these two behaviors was not as evident. Ultimately, for the particular agent tested in the ABM, the use of space heater and personal fan was generally insignificant. Figure 4.15 is an ABM output graph (the behavior trend graph in Section 4.3.4.2) that gives an insight on how much the behaviors are executed throughout the year. All behaviors simulated in the experiment has a set of plots – the graph on the left plots hours of the year on the x-axis and the control values (as seen on Table 4.2) on the y-axis, the one on the right plot the months on the x-axis and the count of hours when behaviors are observed on the y-axis. The

plots indicate that the space heater (a) and personal fan (b) use behaviors are the least observed among all the behaviors.

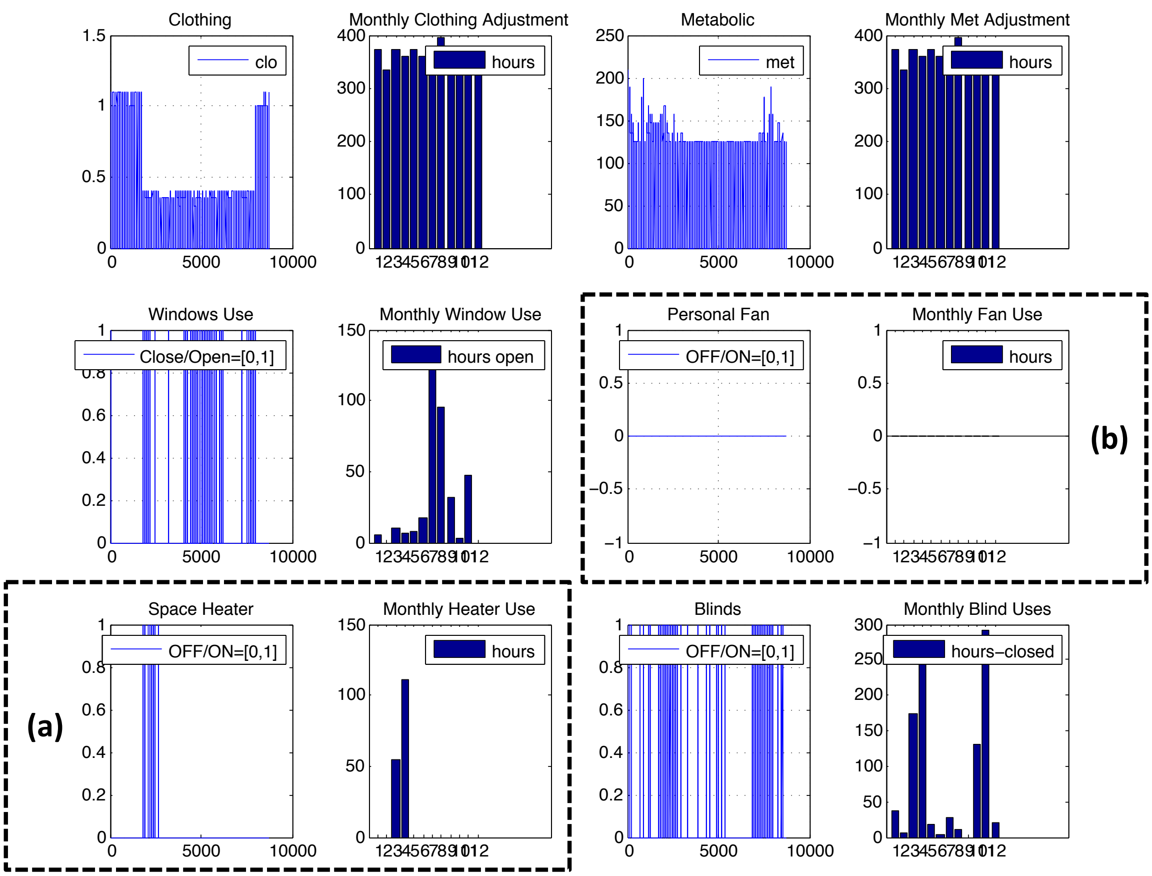


Figure 4.15 Hourly behavior values and monthly hours of executed behaviors

4.3.4.4. Case Study #2 – Optimized behaviors

From results of case study #1, a hierarchy of the five behaviors was made – optimized for comfort and energy savings – in order to see how the ABM responds to the different sets of behaviors. Table 4.5 summarizes two sets of behaviors that are ranked to be most advantageous for either energy savings or comfort. The ranking simply reflects the results in Table 4.4 (column 2 for energy and column 4 for comfort). Based on these rankings, the two sets of behaviors were assigned incremental control belief values (from 0.3 to 0.7), so that there is a distinction among all the behaviors.

Table 4.5 Behavior sets optimized for energy savings and comfort (Philadelphia, PA)

Rank	Energy Performance	Comfort Performance	Control Belief
1	Fan/Heat	Met	0.7
2	Blinds	Window	0.6
3	Clo	Clo	0.5
4	Met	Fan/Heater	0.4
5	Window	Blinds	0.3
EUI (kBtu/ft^2)	**59.23**	**60.14**	
% Hours Comfortable	**68.7%**	**68.9%**	

Table 4.5 also shows the energy and comfort implications of the two behavior sets. With an intention to save energy, the first set (second column in Table 4.5) yielded EUI of 59.23 kBtu/ft^2, which is slightly less than the set with an intention to increase comfort performance (third column in Table 4.5), which resulted in 60.14 kBtu/ft^2. On the other hand, the latter performed slightly higher in terms of the overall comfort level – around 0.2%. The experiment only tested two of many possible options; hence, the ABM provides the capabilities to compare and optimize the set of behaviors that best suit the goal of agents – e.g., maximize comfort, maximize use of natural ventilation, minimize changes in activity level, etc. Figure 4.16 illustrates the results – comparison of EUI and comfort level – of all the experiment cases covered in the experiment (Table 4.4). The case referring to ‘Reference (Default)’ uses the settings that EnergyPlus provides with default behavior inputs.

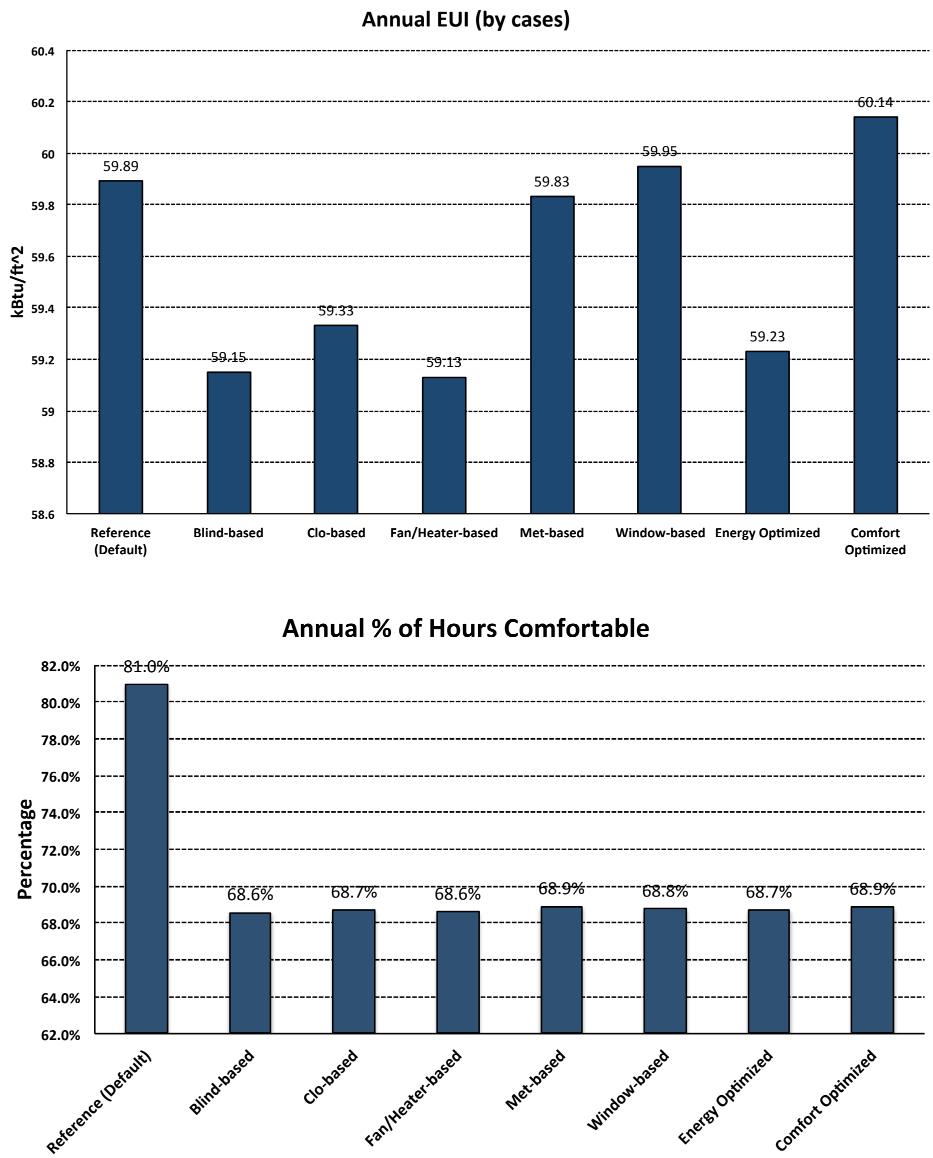


Figure 4.16 Comparison of all the experiment cases for energy use (EUI) and comfort level

4.3.5. Results and Discussion

Simulating multiple occupant behaviors in an operating building was presented using an agent-based modeling approach. ABM discussed in the experiment is an open-architecture program, which can be adaptive to different climate conditions, building functions, and the like by providing a list of user-defined input variables to control the agents. It can also populate simulation results catered to different agent goals in the building. Despite the absence of measured data for validation, the learning/training function of the ABM allows for agents to adapt to the given environment and make reasonable behavior decisions based on their comfort level. Therefore, the simulation results pertaining to individual behavior patterns are assumed to be robust enough to explain those of the building as a whole.

The ABM approach to simulate occupant behaviors is still at its early stages. Nevertheless, as the ABM evolves with further development, we envision that it would help to understand occupant behaviors in buildings, increase the prediction accuracy of anticipated building energy uses, and ultimately help to improve building simulation capabilities.

4.4. ABM Sensitivity Analyses

4.4.1. Sensitivity to Different Weather Conditions

Comparable to case study #2 in the previous section, an optimized set of behaviors for comfort and energy performance was tested for different locations, which depict a spectrum of climatic conditions besides the initial Philadelphia weather – e.g., hot (Phoenix, AZ), cold (Calgary, Canada), and temperate (San Francisco, CA). The goal of the experiment is to test the competence of the ABM by seeing if the results are intuitively valid, as the experiment does not actually validate the results through case studies of actual buildings. Based on the assurance, the experiment is to uncover other research questions that pertain to occupant behavior that the ABM could potentially address. Analyses on behavior priority for the three climates are shown in Figure 4.17.

Based on these results, exclusively on randomly sampled agents (as they are not representative of the general population), ABM results for San Francisco, Phoenix, and Calgary are summarized in Table 4.6, Table 4.7, and Table 4.8, respectively.

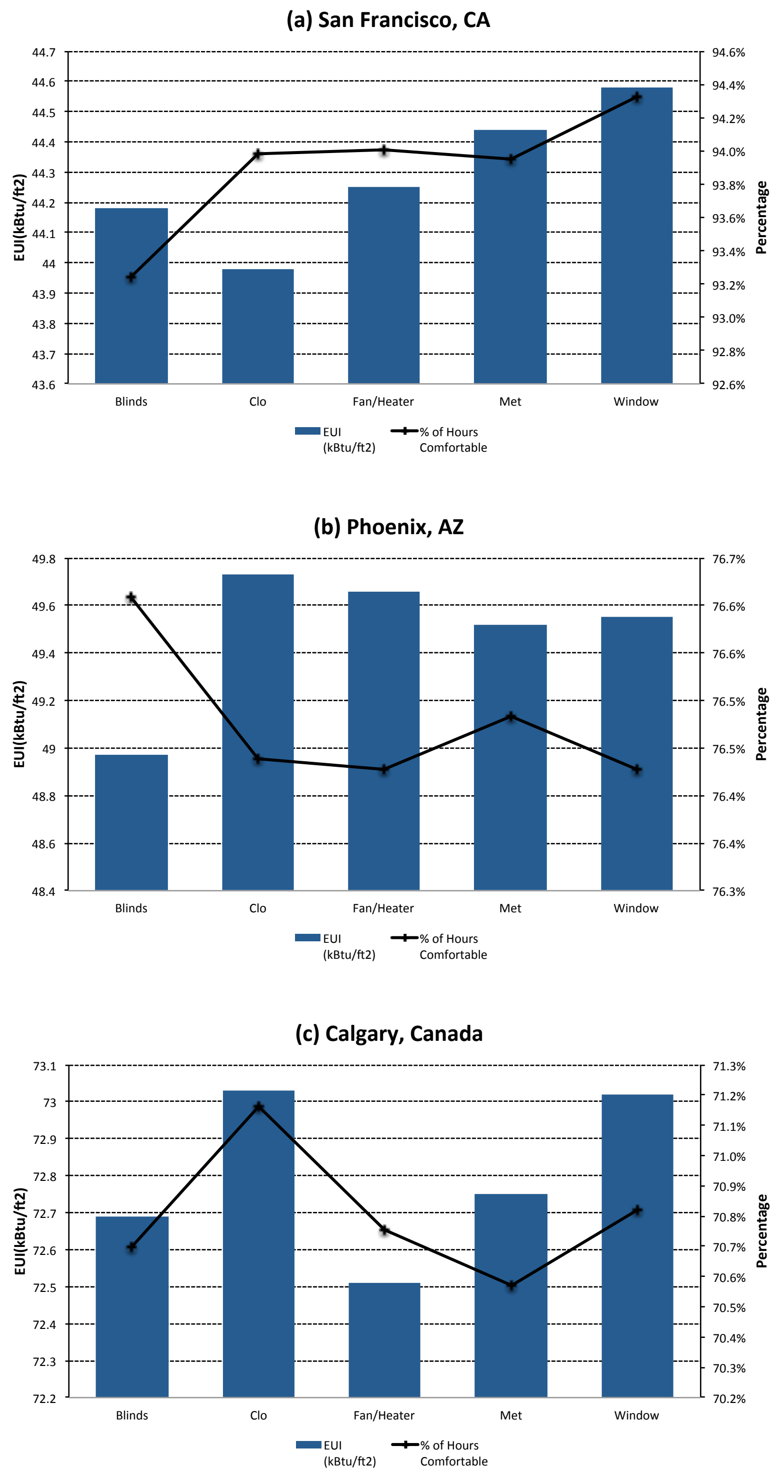


Figure 4.17 Comfort and energy performance ranked by behaviors (a) San Francisco, (b) Phoenix, and (c) Calgary

Table 4.6 Behavior sets optimized for energy savings and comfort (San Francisco, CA)

Rank	Energy Performance	Comfort Performance	Control Belief
1	Clo	Window	0.7
2	Blinds	Fan/Heater	0.6
3	Fan/Heater	Clo	0.5
4	Met	Met	0.4
5	Window	Blinds	0.3
EUI ($kBtu/ft^2$)	**45.62**	**44.92**	
% Hours Comfortable	**94.7%**	**94.4%**	

Table 4.7 Behavior sets optimized for energy savings and comfort (Phoenix, AZ)

Rank	Energy Performance	Comfort Performance	Control Belief
1	Blinds	Blinds	0.7
2	Met	Met	0.6
3	Window	Clo	0.5
4	Fan/Heater	Fan/Heater	0.4
5	Clo	Window	0.3
EUI ($kBtu/ft^2$)	**49.15**	**49.48**	
% Hours Comfortable	**76.5%**	**76.3%**	

Table 4.8 Behavior sets optimized for energy savings and comfort (Calgary, Canada)

Rank	Energy Performance	Comfort Performance	Control Belief
1	Fan/Heat	Clo	0.7
2	Met	Window	0.6
3	Blinds	Fan/Heater	0.5
4	Window	Blinds	0.4
5	Clo	Met	0.3
EUI ($kBtu/ft^2$)	**72.92**	**72.5**	
% Hours Comfortable	**70.8%**	**70.7%**	

The results from the ABM indicate that a temperate San Francisco weather ranked the highest in terms of the level of agent comfort (~95%), while the Philadelphia weather where varied seasons exist ranked the lowest (~69%). As expected, the San Francisco weather ranked the highest in energy performance, with a yearly EUI of around 45 kBtu/ft^2, and the coldest weather conditions among the four, Calgary, ranked the lowest, with a yearly EUI of around 73 kBtu/ft^2. The implications of the ABM include the following:

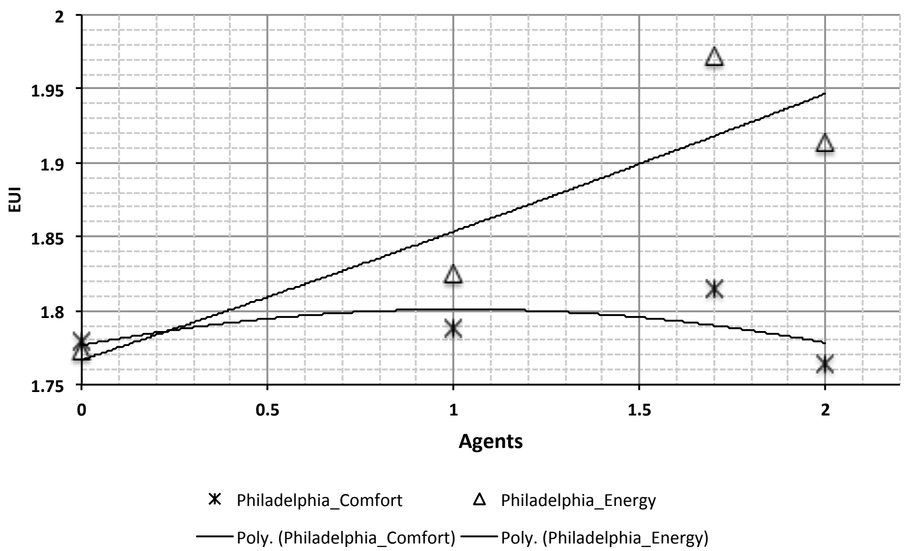
- Overall comfort level of agents is higher in homogenous climates, rather than in those with discrete seasons.
- Blinds are effective in both comfort and energy performances in a hot climate.
- Energy used for heating seems to be higher among other means to address the thermal conditions.
- In a hot climate, controlling the solar radiation was more effective than controlling air movement for both comfort and energy performances. However, these observations are exactly the opposite for a cold climate.

4.4.2. Sensitivity to Different Agent Populations

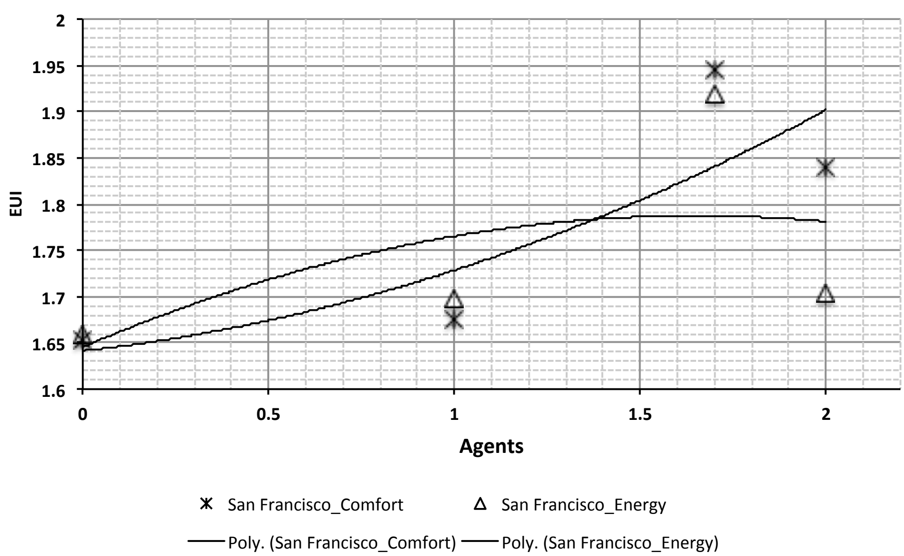
While the previous case studies were based on the behavior decision-making process of a single agent, the case study presented here looks at the ABM sensitivity to multiple agents. ABM results for a single agent are compared with those that have a reasonable number of agents (10 agents), are overcrowded (50 agents), and are extremely overcrowded (100 agents) in the given space[7]. Figure 4.18 compares the number of agents tested in the ABM and the yearly EUI for the four sites studies in the previous case study. Figure 4.19 compares the number of agents tested in the ABM and the percentage of hours (yearly) that achieved agent comfort level for the four sites.

[7] The increased number of agents assumes a multiplication of the single agent, instead of aggregating the behaviors of multiple autonomous agents, due to the absence of a robust validation process for the existing ABM methodology.

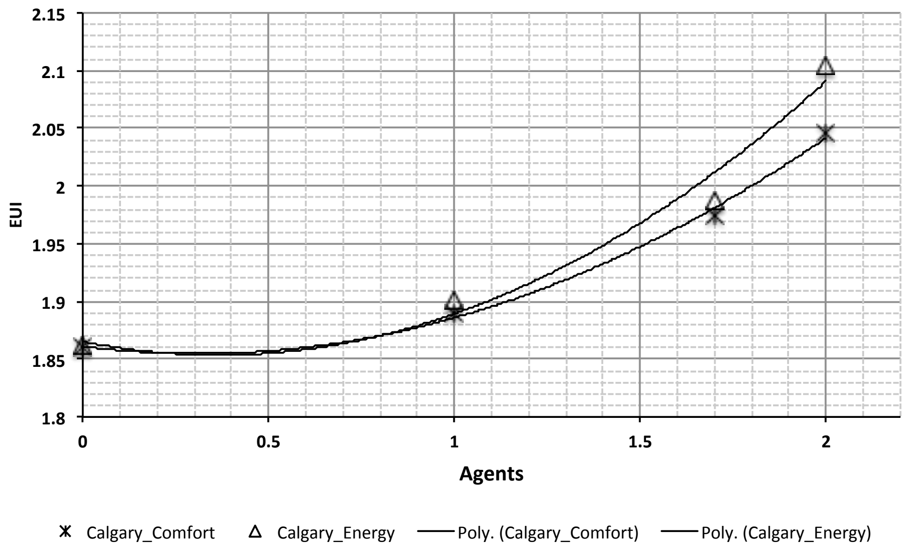
(a) Philadelphia



(b) San Francisco



(c) Calgary



(d) Phoenix

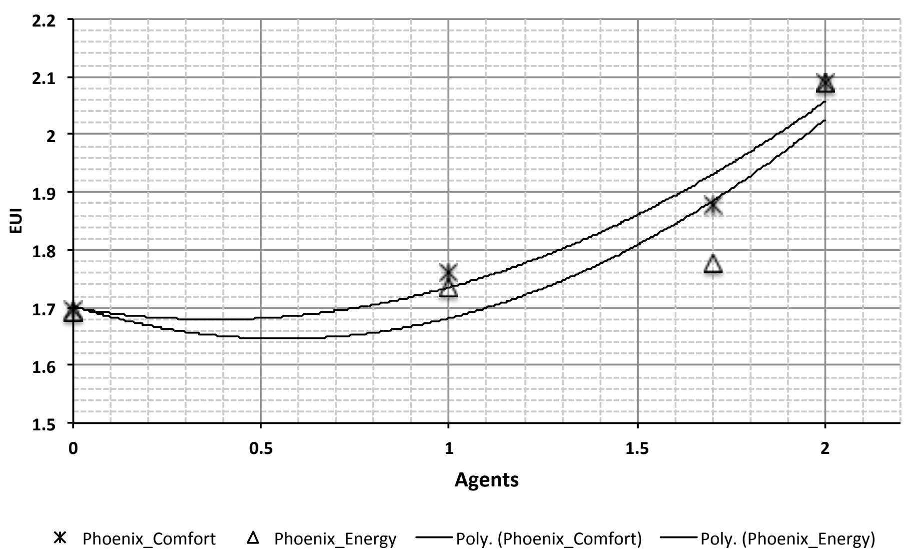
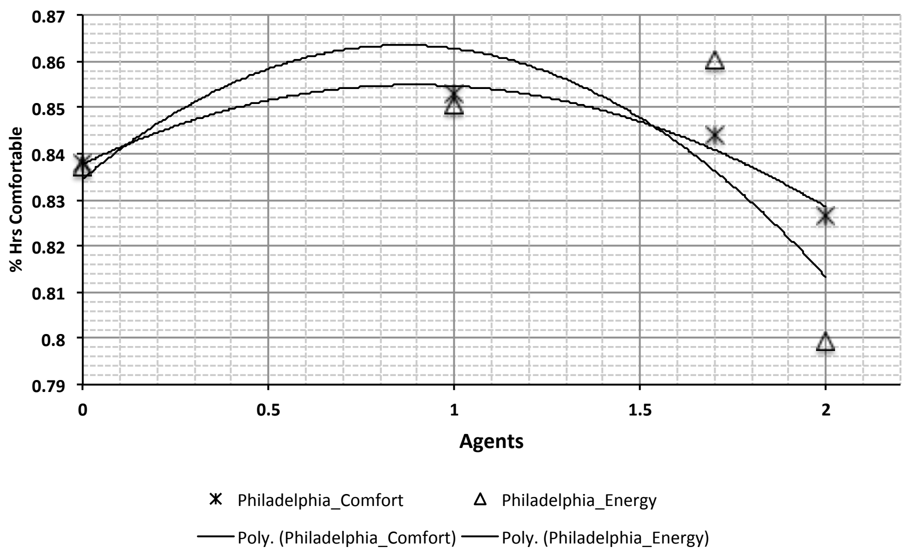
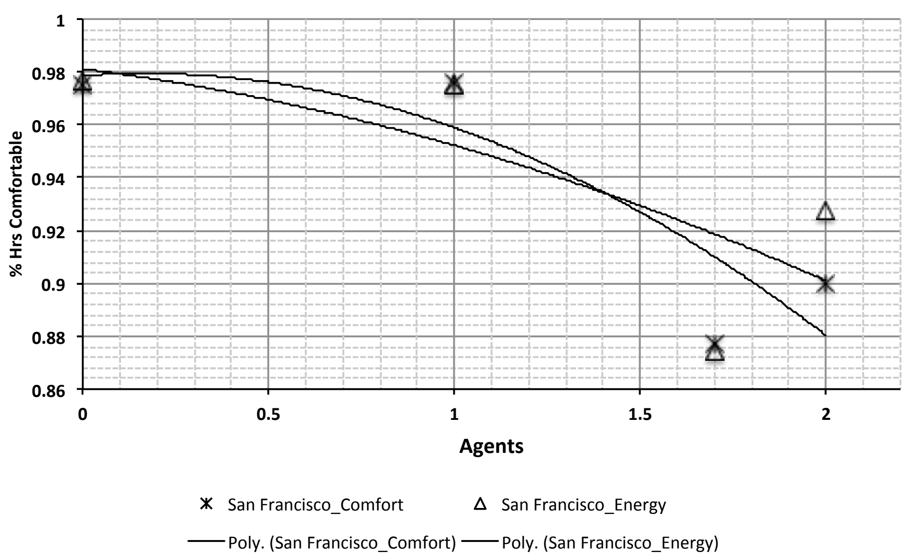


Figure 4.18 Agent number and EUI (logarithmic scale)

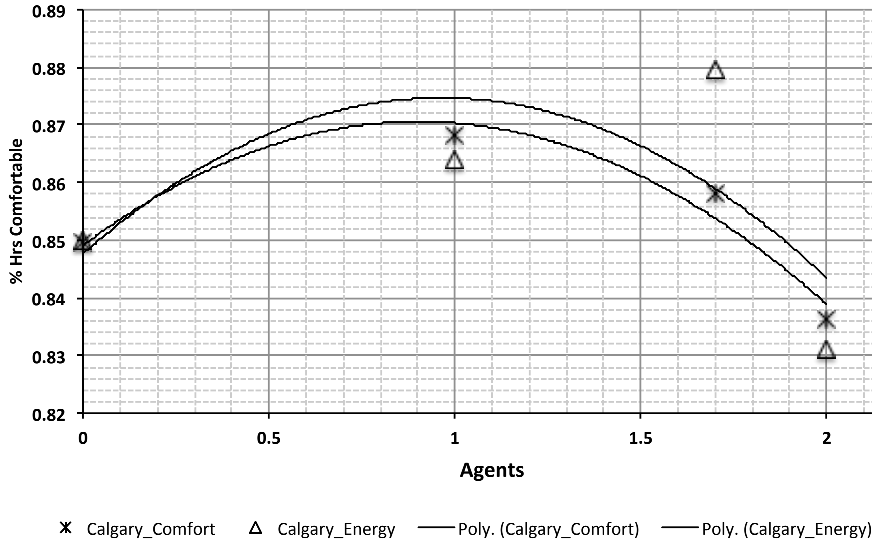
(a) Philadelphia



(b) San Francisco



(c) Calgary



(d) Phoenix

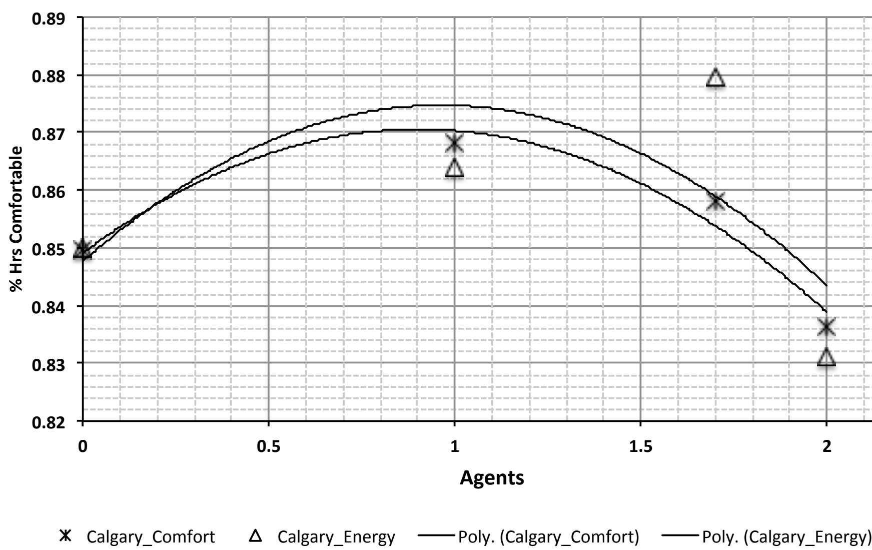


Figure 4.19 Agent number and % hours comfortable (logarithmic scale)

The findings imply that:

- In Phoenix and Calgary, which are typically categorized as either hot or cold climates, a linear relationship between agent number and energy use is observed. This is in accordance with common sense, as occupants are considered to be heat generators in the space.

- However, Philadelphia and San Francisco results show that the energy use dropped when agents in the space were exponentially increased to hundred agents. The observation is rather counterintuitive, so the monthly energy use as part of the ABM output was investigated, in Figure 4.20, which shows that the overall heating energy in the space is decreased due to the increased number of agents.

- For comfort, most climates showed a bell curve with the maximum comfort level reached when agents were around 10 per zone. The only exception was in a temperate climate, such as, San Francisco, where consistent drop of comfort level resulted as the number of agents increased.

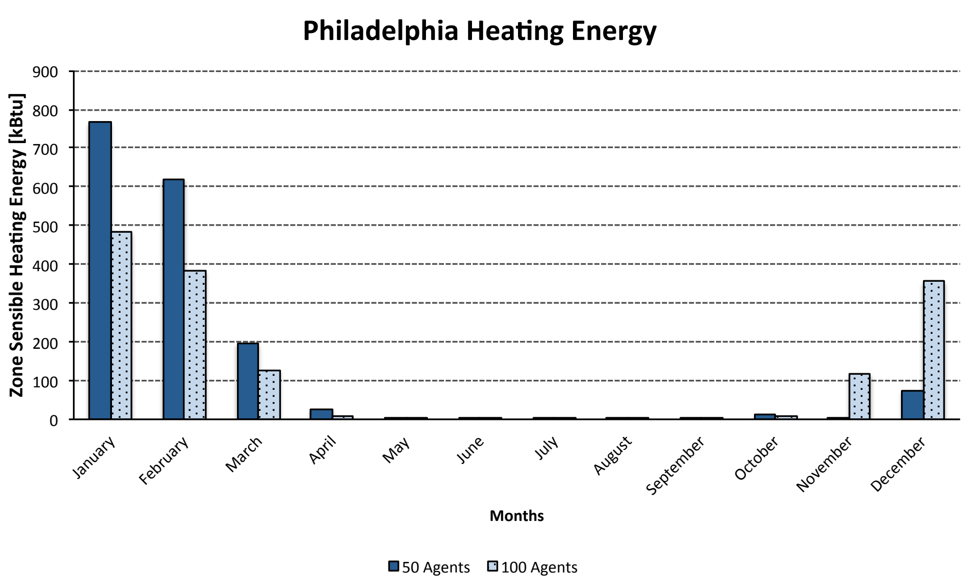


Figure 4.20 Heating energy per number of agents for Philadelphia

4.4.3. Sensitivity to Multi-Zone Space

One of the limitations of applying ABM in EnergyPlus is the inability to conduct location-based simulation. In other words, it is not possible for current EnergyPlus capabilities to distinguish most environmental parameters, except daylight levels, based on the specific location of agents within the same space (or zone). To account for different agent location, an experiment is conducted by dividing the zones in the space to emulate the different thermal conditions, as in Figure 4.21.

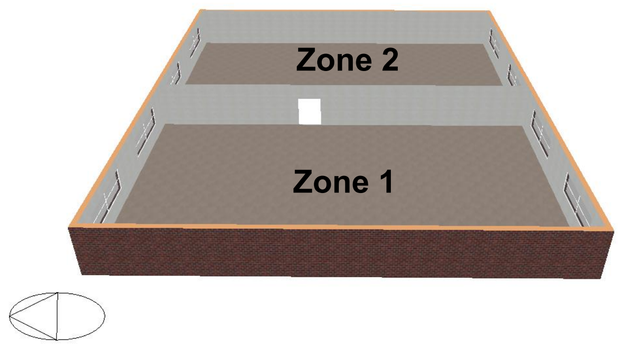


Figure 4.21 Space configuration for the multi-zone ABM experiment

The idea is to observe the consequences of dissimilar behavior decisions in the space. Along with the space configuration, the following summarizes the changes in the simulation setting:

- Number of agents: 5 per zone (total of 10 agents are chosen as a result of Section 4.4.2).
- Clothing and activity levels are assumed to be the same in both zones.
- Occupancy schedule is assumed to be the same in both zones.
- For a simple experiment, all normative behaviors are excluded from the experiment.
- Behavior decisions in Zone 1 are prioritized, allowing agents in Zone 2 to be more sensitive to the changes in their microclimate, which is analogous to the ‘leader-follower’ relationship [Silverman et al., 2007].

First, the ABM simulated the two-zone space in Philadelphia. Figure 4.22 is the behavior trend graphs for Zone 1 and Zone 2. Besides clothing, activity, and space heater use, most behaviors seem to show different levels of frequency and degree of changes throughout the year.

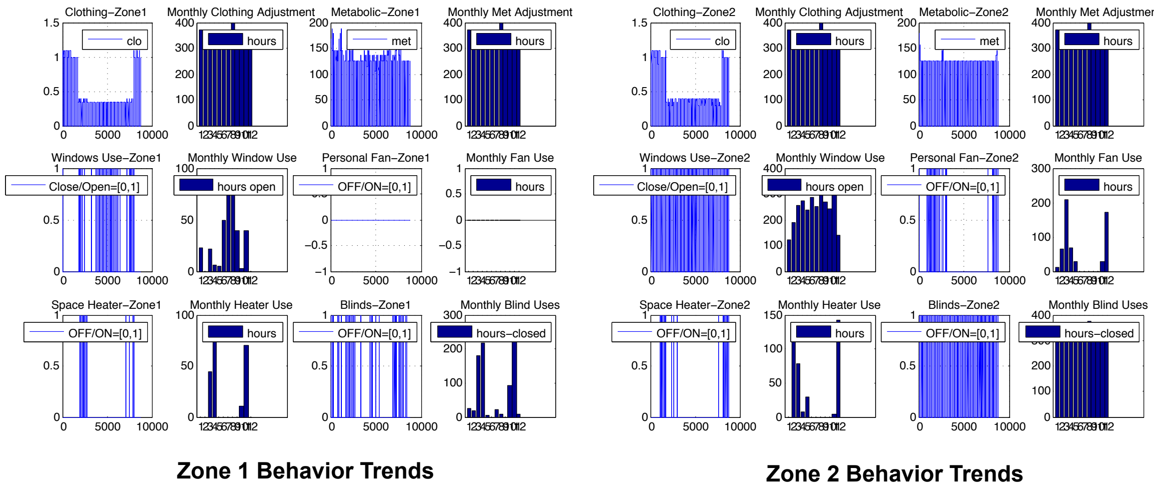


Figure 4.22 Comparison of behavior trends between Zone 1 and Zone 2 (Philadelphia)

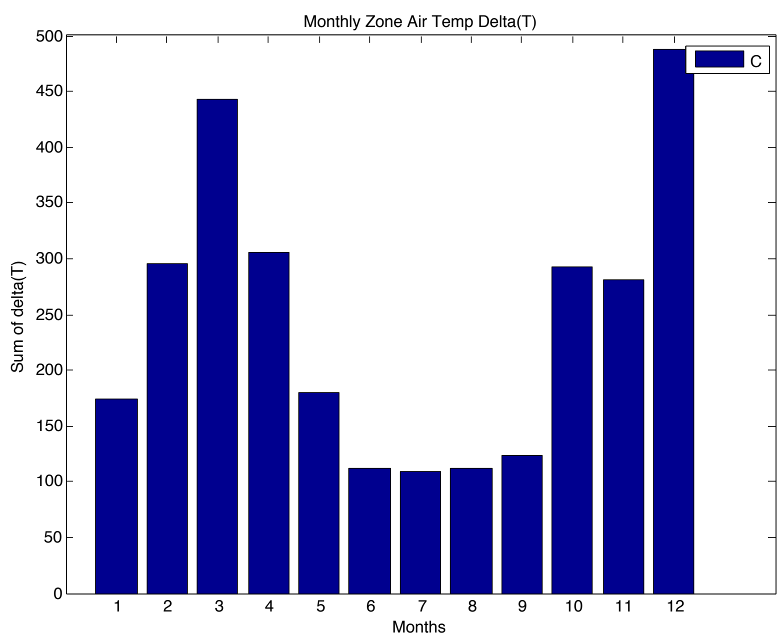


Figure 4.23 Monthly sum of zone air temperature differences between Zone 1 and Zone2

To compare the behavior impact on the thermal conditions of the space, hourly zone air temperature differences are plotted (summed per month) as shown in Figure 4.23. Noticeable temperature differences are observed during the colder and transitioning months, i.e., agents are mostly influenced by behaviors of others (as a result of the behavior impact on the thermal condition rather than normative influences) during these months and least affected in hotter months.

In terms of energy performance, four different simulation cases discussed in the dissertation are compared, shown in Figure 4.24. SZ Energy and SZ Comfort refer to the single zone ABM cases that were optimized for energy and comfort, MZ Default refers to the multi-zone test case without behavior inputs, and MZ ABM refers to the experiment explained in this section. The results show that the last test case yield the best energy performance, implying that behavioral diversity in a space can have a positive impact on reducing energy uses.

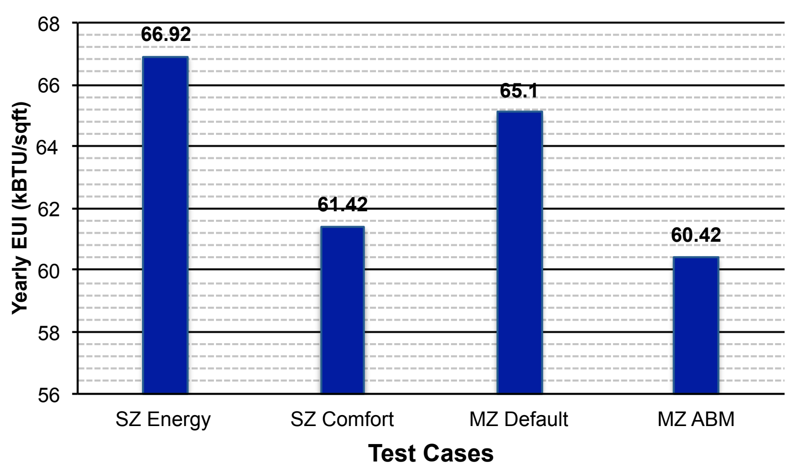
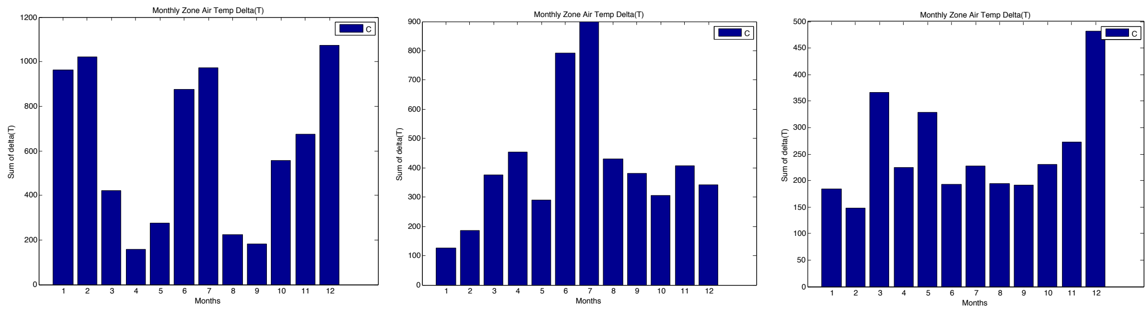


Figure 4.24 Annual EUI for different test cases

While the findings mostly concern the Philadelphia climate, other climate conditions reveal different multi-zone ABM results. As an example, the zone air temperature differences are shown



Monthly Sum of Delta(T) - SF **Monthly Sum of Delta(T) - Calgary** **Monthly Sum of Delta(T) - Phoenix**

Figure 4.25 Monthly sum of zone air temperature differences between Zone 1 and Zone2 for San Francisco, Calgary (Canada), and Phoenix

for three other climate conditions (San Francisco, Calgary (Canada), and Phoenix) in Figure 4.25. The greatest temperature difference as a result of the diverse behavior decisions was observed in the temperate San Francisco climate, and the smallest in Philadelphia. Interestingly, the monthly trends for the summed temperature differences are different in all four climates.

Table 4.9 is a comparison of energy and comfort performances of the four climate conditions and single/multi-zones tested in the ABM. In general, the two-zone experiment simulation resulted in increased energy performance, except for San Francisco. According to the behavior trend graphs (details in Section 4.3.4.2) of San Francisco, in Figure 4.26, behaviors in Zone 1 seem to incur a significant increase in the space heater use behavior, which could potentially explain the increased energy consumption. In general, the behavior diversity was not effective in comfort performance; most case studies in a multi-zone space showed a decrease in the total % hours of comfort.

Table 4.9 Comparison of energy and comfort performances by climate conditions and zone division

	Single Zone (kBtu/sqft)		Two Zones (kBtu/sqft)	Single Zone (% hours comfortable)		Two Zones (% hours comfortable)
SITE	Energy Optimized	Comfort Optimized		Energy Optimized	Comfort Optimized	
Calgary	79.74	77.56	80.35	73.13%	73.82%	69.70%
Phoenix	54.44	57.79	51.79	75.40%	74.25%	74.57%
Philadelphia	66.92	61.42	60.42	70.89%	71.29%	67.31%
San Francisco	49.95	47.31	59.5	94.38%	94.62%	89.86%

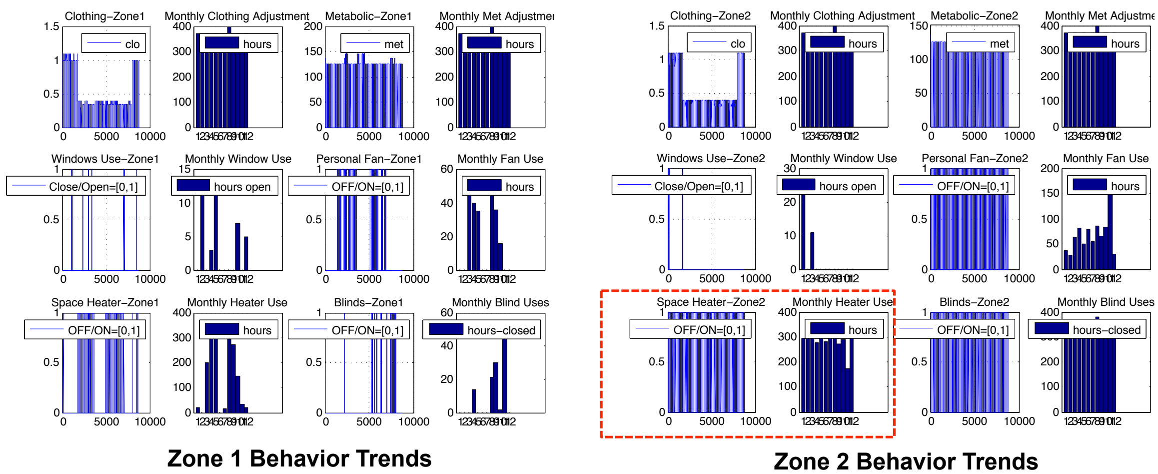


Figure 4.26 Comparison of behavior trends between Zone 1 and Zone 2 (San Francisco)

5. CONCLUSION

The dissertation underscores the importance of occupant behaviors as one of the key elements that dictates the energy uses in an operating commercial building. An energy-efficient building starts with understanding occupant behaviors and behavioral implications on energy performance. In a typical building design process, building energy simulation programs are primarily responsible for helping architects and engineers to make design decisions that increase energy performance. However, because current simulation capabilities do not account for realistic occupant behaviors, they underestimate the actual energy consumption observed in buildings. Hence, the dissertation's effort was to come up with a new methodology that addresses the shortcomings of current simulation programs, and to find opportunities to increase the accuracy of building energy simulation results.

The study in the dissertation was undertaken to account for realistic building occupant behaviors, and to find a simulation process that calculates the dynamic influences of the behaviors in a given space. Because the scope of the dissertation did not include case studies of actual buildings and collecting of measured data, constructing a robust human behavior model to measure and predict occupant behaviors emerged as an urgent task. Therefore, the early phase of the dissertation was predominantly invested in finding a prominent theoretical framework that would suffice as a competent human behavior model. As a result, the dissertation has adopted the reasoned action model and the adaptive comfort model to explain the behaviors commonly observed in buildings. The next challenge was to simulate the findings learned from the human behavior model. The research conducted its building energy simulation through EnergyPlus, which is one of the most rigorous simulation programs for calculating building thermodynamics and energy consumption. However, the shortcomings of the program made it difficult to fully accomplish the research goals, which were to simulate real-time behavior changes from individual occupants. These occupants are believed to make behavior decisions based on the dynamic changes of the thermal conditions of a space rather than relying on a predetermined historical data. Also, the behavior influences on the thermal conditions of a space needed to be the feedback for making consecutive behavior decisions. To address the limitations of existing simulation programs, the dissertation introduced an agent-based modeling approach in conjunction with simulation coupling, which is a new simulation methodology that addresses occupant behaviors.

The agent-based modeling approach for simulating occupant behaviors has shown that uncertainties of occupant behaviors can be accounted for and simulated, lending the potential to augment existing simulation methods. In general, real-world building occupant behaviors are closely correlated to an individual's comfort level. Hence, the occurrences of behaviors are directly affected by environmental parameters, such as the zone air temperature, outside air temperature, humidity, air speed, and relevant climatic influences. While the existing simulation methods rely on deterministic behavior input information, the ABM in the dissertation responds to the constant changes of the surrounding environment, capturing the impact of behaviors on the thermal conditions of a space, which also incurs added environmental changes that result in dissimilar behavior patterns (compared to those of existing simulation results). For an agent in Philadelphia, comfort-driven occupant behaviors resulted in higher energy consumption, which suggests the limitations of passive measures in mitigating the thermal discomfort. The effectiveness of behavior varies depending on the agent goal and climate. The two agent goals used in the research were to optimize agent comfort or overall energy performance, with four climate characteristics considered for comparison (Philadelphia, San Francisco, Phoenix, and Calgary). Increasing the number of occupants in a space tends to increase the internal load, as occupants function as metabolic heat generators, increasing the total energy load. However, the increased heat load turned out to be helpful in reducing the heating load in some climates, which helped to decrease the overall building energy consumption. Finally, varying behavior decisions in the same zone not only created a different microclimate around the occupant, but they helped to save overall building energy.

The findings of the research were extracted from a series of simulation experiments applying the methodology discussed in the dissertation. The following explains the contribution and limitations of all the experiments.

First, the experiment on the ‘dynamic schedule’ helped to understand that all behavior-related inputs are controlled through the various schedules (e.g., occupancy, light use, blind use, window use, etc.) in a typical building simulation program. However, most simulation practices have been investing little effort in matching the schedules that reflect the reality. Hence, the experiment nurtured an interest to making predictions of occupant behavior that closely mimic actual occupants, and incorporating these behavior inputs into building energy simulation programs.

The second experiment investigated the potentials of agent-based modeling as a framework to predict and simulate occupant behaviors. Agent-based modeling has been frequently used to simulate crowd behaviors in the building context (such as pedestrian movement and evacuation), but the research in trying to link behaviors and energy performance was a pioneering effort. As a result, the experiment was able to simulate a single window-use behavior in a naturally ventilated office space. The experiment illustrated the thermodynamics of a space that distinguished itself from those of an existing EnergyPlus simulation. The results were promising as they had reinforced the hypothesis that subtle behavior changes could affect the microclimate of an occupant. In terms of energy consumption, the simulations settings were simple enough for the agent-based modeling to yield results comparable to an existing EnergyPlus simulation. On one hand, the experiment was successful in validating the agent-based modeling approach as a robust method that parallels the EnergyPlus in a simple simulation exercise. However, the simplicity and assumptions of the experiment (as discussed in Section 4.2) made it difficult assert that the agent-based modeling was better than the existing simulation approach, hence, the limitations of the experiment.

For the next iterations of experiments, the intentions were to increase the complexity, while reducing the uncertainties as much as possible. Thus, the third experiment began to incorporate multiple occupant behaviors and allowed the agent-based modeling to reveal emerging behavior phenomena. Although the experiment was based on the conviction that the agent logic was ‘good enough’ and the results seemed convincing and/or intuitive, a comprehensive validation process was fundamentally missing and the experiment could not substantiate the findings. Therefore, the agent-based modeling in the dissertation was overhauled to function as an open-architecture framework so that it could cater to specific user purposes and be applicable to a general audience. On that note, the last experiments were concerned with numerous sensitivity studies of comparing various input variables of the open-architecture agent-based modeling. The objective was to gain insight on occupant behaviors and behavior related building dynamics. In addition, the experiments were to identify both the contingent errors of the agent-based modeling and new research questions related to occupant behaviors. While the first helped to fine-tune the proposed methodology, the latter introduced interesting links between occupant behaviors and unconventional variables, e.g., climate, behavior diversity, agent number, etc. At the end of the day, the main contribution of the dissertation is the new simulation methodology that strives to make predictions of realistic occupant behaviors in buildings, calculates the behavior influences on building energy performance and occupant comfort level, and ultimately produces promising results that potentially could help increase the accuracy of building energy simulation programs.

This research has fomented many questions in need of further investigation. First, the need for a location-based simulation method is crucial in fully implementing the agent-based modeling (and, in particular, the agent-base mindset). Second, some form of a validation through measured data – e.g., a comprehensive occupant survey as proposed in Appendix B or case studies of an existing building – will help to calibrate the agent-based modeling algorithms. Finally, the full effect of occupant behaviors that incorporates the normative beliefs, which was largely missing in the dissertation, will help the agent-based modeling approach to emulate true to life occupant behaviors. Aside from improving the prediction accuracy of building energy simulation programs, the research could assist architects to promote a specific behavior to maximize energy or comfort performances – a new paradigm for the performance-based design process. Ultimately, the research envisions a user-friendly interface for the general audience to instigate the importance of occupant behaviors in daily building operations, and to offer an interactive tool to quantify the behavior influences (or other influences on behaviors) through simple simulation exercises.

APPENDIX A. Summary of current human behavior research

Table A.1 summarizes the most commonly studied behaviors in the literature, with a set of common questions identified in explaining the research results.

1. When do you initiate behavior?

2. How long does it last?

3. What triggers the behavior?

4. How do you define the behavior?

5. What are the effects of the behavior?

6. Miscellaneous information?

Table A.1 State of the art in current human behavior research

	Window Use/Control	**Blind Use/Control**
1	- Closely related to comfort.[1]	- Static visual glare, overheating criteria.[1] - Avoid direct sunlight and overheating (South façade).[2]
2	- Until the room is sufficiently cooled for the occupant to feel discomfort (Based on NV buildings).[1] - Mostly during operation hours, while windows are closed at the end of the day.[2]	- East façade: Linear (proportionate) relationship between shading % and solar radiation (Global vertical irradiance [$W.m^{-2}$].[4] - South façade: 75% shading regardless of solar radiation levels.[4] - North façade: 10% shading regardless of solar radiation levels.[4]
3	- IAT for opening and proportional control.[1] - OAT for opening behavior.[2,4] - IAT and neutrality temperature.[3] - Yun and Steemers' Model: IAT, occupancy, and previous window state.[4]	- Annual profiles of user occupancy and work plane illuminance.[1] - Solar radiation intensity (and sun position).[3]
4	- Open, closed, and tilted.[1,2,4]	- 0% (no blinds deployed) to 100% (full shading).[4] - Lightswitch2002: Mean blind occlusion on weekdays (%).[1]
5	- Mixing of indoor/outdoor air.[1] - Drop in IAT when OAT is low.[1]	- Reduces the solar gain in the summer, hence, increase the heating energy demand.[5]

	- Achieve higher air exchange rate.[2] - Reduce overheating by night ventilation.[2]	
6	N/A	- Two user behavior characterization:[1] 1. Dynamic manual blind control: blinds fully lowered as soon as incoming direct solar irradiance above 50Wm^{-2} hits the workplace. The slat angle is the smallest of either 0, 45, 75 degrees (facing out downwards). 2. Static manual blind control: blinds permanently fully lowered (slat angle of 75).

	Lighting Use/Control	
1	- Commonly assumed to start with occupancy.[1]	- Darkness of the room as a whole, inadequacy of daylight on visual tasks, or a combination of these and other factors.[2]
2	- Until people vacate the space.[2,3]	- People hardly turn off the light switch during the period of occupation.[2]
3	- Occupant arrival, departure and temporary absenteeism.[4] - DAYSIM: Radiance-based stochastic model.[1] - Algorithm input: occupancy, work plane illuminance, and irradiance.[1] - Minimum working plane illuminance levels less than 100 lux lead to significant increase of switching 'on' probability.[2,5] - Low workstation illuminance levels (measured horizontal task illuminance levels well below 200 lux) appear to trigger a non-random increase in probability of switching the lights on upon occupants' arrival in their offices/workstations.[6]	- Hunt Algorithm[2]: • An overall level of 150 lux (the level provided by the artificial lighting in the school classrooms) produced an 18% probability of requiring extra light. • At 500 lux (recommended artificial lighting level for shallow offices) this probability was negligible (<1%). • Less than 50% artificial light use when the internal daylight level (over the whole of the working plane) exceeded 300 lux and none used when it exceeded 1200 lux
4	- Lights ON/OFF, and various dimming.[7]	- Lightswitch2002 control value: Mean electric light load on weekdays (%).[1]
5	- Active daylight users result in savings in artificial light use.[1]	- Helps to decrease the cooling load, while increasing the heating load at the same token.[7]
6	- SHOCC: Specific user group assigned to control over specific entities:[1] • User does not consider daylight: Switch on light upon arrival leaves it on regardless of the work plane illuminance [lux].	• User considers daylight: Follow Hunt's model. - Active and passive daylight user.[4]

	Thermostat/HVAC Use/Control	**Occupancy/Schedule**
1		- From arrival time of each occupant
2		- Until departure time of each occupant
3		- SHOCC population predictor and Lightswitch2002

		Algorithm.[1] - ASHRAE Standards.[2] - Newsham's stochastic model (occupant arrival, departure, and temporary absenteeism).[3] - Preset occupancy/schedule. - Occupancy prediction by Markov chain.[4]
4		- Occupy, leave, or intermediate leave.[3,5]
5	- Setpoint temperature changing with the running mean of the outdoor temperature result in substantial savings in energy use without increasing occupant discomfort [Nicol and Humphreys, 2002]	- Annual average metabolic heat injection of 128 kWh, where their laptop accounts for additional 72 kWh.[6] - Primary importance in considering all other human behavior models.[4,5,7,8] - For intermittent human activities, a weighted average metabolic rate is generally satisfactory, which is approximately 75 W/m^2. [9]
6	N/A	- Detailed study in the 'Occupancy/Dynamic Schedule' section.

	Space Heater/Personal Fan	**Thermostat Setpoint**
1		
2		
3	- Closely related to indoor and outdoor temperature.[1]	
4	- Turn ON/OFF. [1]	
5	- Increased heat gain and energy consumption. - Higher air movement to cause drop of indoor temperature of 4°C for fans. [1]	- Setpoint temperature changing with the running mean outdoor temperature can:[1] • Not increase occupant discomfort compared to constant setpoint. • Result in substantial savings in energy.
6	- Prediction algorithms using the logit function is available. [1]	- Federal guideline for thermostat setpoint:[2] • Heating: 68 °F • Cooling: 78 °F

Window Use/Control	Blind Use/Control	Lighting Use/Control	Occupancy/ Schedule	Heater/Fan	Thermostat Setpoint
1. Rijal et al., 2007 2. Herkel et al., 2005 3. Auliciems, 1981 4. Haldi & Robinson, 2009	1. Reinhart, 2004 2. Rubin et al., 1978 3. Lindsay & Littlefair, 1992 4. Mahdavi & Pröglhöf, 2009 5. Rijal et al., 2007	1. Reinhart, 2004 2. Hunt, 1979 3. Pigg et al., 1996 4. Newsham et al., 1995 5. Lindelöf et al., 2006 6. Mahdavi & Pröglhöf, 2009 7. Bourgeois et al., 2006	1. Reinhart, 2004 2. ASHRAE Std. 90.1-2004 3. Newsham et al., 1995 4. Page et al., 2008 5. Herkel et al., 2008 6. Bourgeois et al., 2006 7. Hunt, 1979 8. Mahdavi & Pröglhöf, 2009 9. ASHRAE Fundamentals, 2005	1. Nichols, 2001	1. McCartney et al., 2002 2. www.eereblogs.energy.gov

APPENDIX B. Survey questions for window use behavior

This survey was created as part of a class assignment for 'COMM 577 Attitude & Behavior Prediction' at the University of Pennsylvania. The survey encompasses the framework of the reasoned action model and the research intentions presented in the dissertation. The survey questions were validated by the course instructor, but they were never taken by real building occupants.

[Background Factors]

- *I am a,*
  - *male ( )*
  - *female ( )*

- *My age group is,*
  - *under 25 ( )*
  - *26 – 35 ( )*
  - *36 – 45 ( )*
  - *46 – 55 ( )*
  - *above 56 ( )*

- *What is the best description of my location at the workplace?*
  - *interior/core ( )*
  - *perimeter (within 5 ft from the windows) ( )*
  - *perimeter (window visible, but over 5 ft away) ( )*
  - *private office ( )*

- *My understanding of building systems and/or sustainability compared to an average person is*[8]
  extremely good (1) (2) (3) (4) (5) (6) (7) extremely bad

[Behavioral Belief]

[8] This question is optional and whether to include or not will greatly be dependent on its significance in the elicitation study.

- ‘Opening the windows’ at the workplace will enhance my thermal satisfaction
  extremely unlikely (-3) (-2) (-1) (0) (1) (2) (3) extremely likely

- *‘Opening the windows’ at the workplace would improve my productivity*
  extremely unlikely (-3) (-2) (-1) (0) (1) (2) (3) extremely likely

[Normative Belief]

- *Most people who are important to me in the workplace would appreciate me ‘opening the windows’*
  extremely unlikely (-3) (-2) (-1) (0) (1) (2) (3) extremely likely

- *How many people similar to me perform ‘opening the windows’?*
  virtually none (-3) (-2) (-1) (0) (1) (2) (3) almost all

[Control Belief]

- *If I wanted to, I could easily perform ‘opening the windows’*
  strongly disagree (-3) (-2) (-1) (0) (1) (2) (3) strongly agree

- *How likely is it that you will be ‘opening the windows’ during the summer season?*
  extremely unlikely (-3) (-2) (-1) (0) (1) (2) (3) extremely likely

- *How likely is it that you will be ‘opening the windows’ during the winter season?*
  extremely unlikely (-3) (-2) (-1) (0) (1) (2) (3) extremely likely

APPENDIX C. User-defined input for ABM

Although the ABM allows an agent to make autonomous design decision, it is an open-architecture framework that provides users' freedom to customize the simulation process to better accommodate their simulation (or agent) goals, location, and constraints. Figure C.1 illustrates a list of user input information. The tables on the left are primarily values related to agent characteristics or building systems, and those on the right refer to agent behavior beliefs is a GSP format adopted from [Silverman et al., 2005].

Number of Agents	2		
Weather File	Philadelphia,PA		
Simulation Days	365	Schedule Input	Dynamic
Simulation Timesteps	1	Total Equipment Added	2
HVAC Category	VAV		

LEGEND
Custom Parameters
Category
User Input

Behavior Beliefs	Behavioral Belief	Control Belief	Normative Belief
Behavior #1=clo			
Behavior #2=met			
Behavior #3=window			
Behavior #4=fan			
Behavior #5=heater			
Behavior #6=blinds			
Behavior #7			
Behavior #8			

	Spring	Summer	Fall	Winter
Initial Clo Value	3	2	3	4
Initial Met Value	3			

	Watt/person	Radiant Coefficient	Air Speed (m/s)
Equipment #1			
Equipment #2			
Equipment #3			
Equipment #4			
Equipment #5			

Blind Type	Interior		(Exterior, interior, or between glass)
Slat Angle	Horizontal		(Horizontal or vertical)
Schedule Control	Comfort		(Comfort, system, or setpoint)
Shading Control	Primary-Indoor Temperature	Secondary-Glare Index	(Schedule, solar incident, solar irradiance, outdoor temperature, glare index, or autmatic)
Shading Setpoint	22°C		(Temperature, W/m^2, or Watt)

Agent Belief		0.25
	Agent belief on comfort	0.6
	Agent belief on efficiency	0.4
Control Belief		0.5
	Distance to Control	0.3
	Accessibility	0.7
Normative Belief		0.25
	Agent Influence	0.5
	Leader	0.35
	Follower	0.65
	Agent Norm	0.5
	Injuctive Norm	0.73
	Descriptive Norm	0.27

COST FUNCTION WEIGHTS	1.00

Figure C.1 Full list of user-defined inputs for ABM

The following tables explain the input values used for the clothing and activity levels. Depending on the input value, minimum, maximum, and increment changes are also defined in the ABM. For example, if an initial clothing level input variable is 2, then the [min,max,increment]=[0.5,0.7,0.1], so that the scope of behavior change associated with clothing level can be reasonably bounded. The same applies to the activity level.

Table C.1 Clothing level categorization [ASHRAE Thermal Comfort (Table 7)]

ABM Input Value	Clothing Detail	Clo value
1	Shorts and t-shirt	0.3-0.4
2	Trousers and shirt	0.5-0.7
3	Light business suit	0.8-1.2
4	Business suit and thermals	1.3-1.7
5	Jacket and overcoat	1.8-2.2
6	Heavy winter wear	2.3-2.7

Table C.2 Metabolic activity level categorization [ASHRAE Thermal Comfort (Table 4)]

ABM Input Value	Activity Detail	Met value
1	Reading, seated	1.0
2	Typing	1.1
3	Filing, seated	1.2
4	Filing, standing	1.4
5	Walking about	1.7
6	Lifting/packing	2.1

APPENDIX D. PMV parameters in the ABM

The following figures explain the various behavior values, their corresponding PMV parameters, how the agent in the ABM perceives/controls them, and how they are interpreted in EnergyPlus.

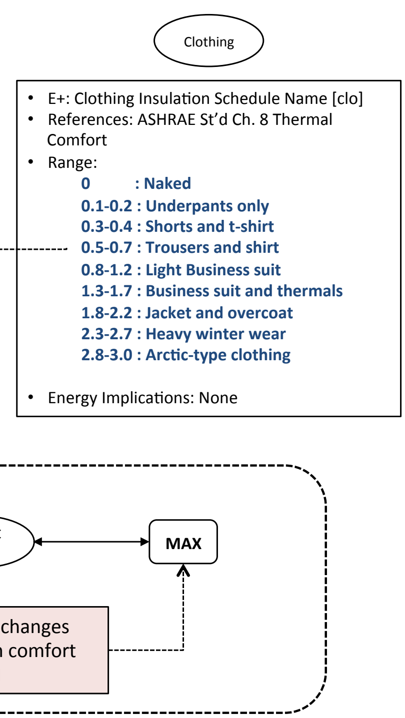
[Clo Level]

Clothing level is predetermined by the user for three seasonal conditions: winter, summer, and transitions (spring and fall) months. Based on the input values, an agent can adjust its clothing level based on the increment defined in the ABM (referenced from ASHRAE Thermal Comfort Standard).

PMV-Clo

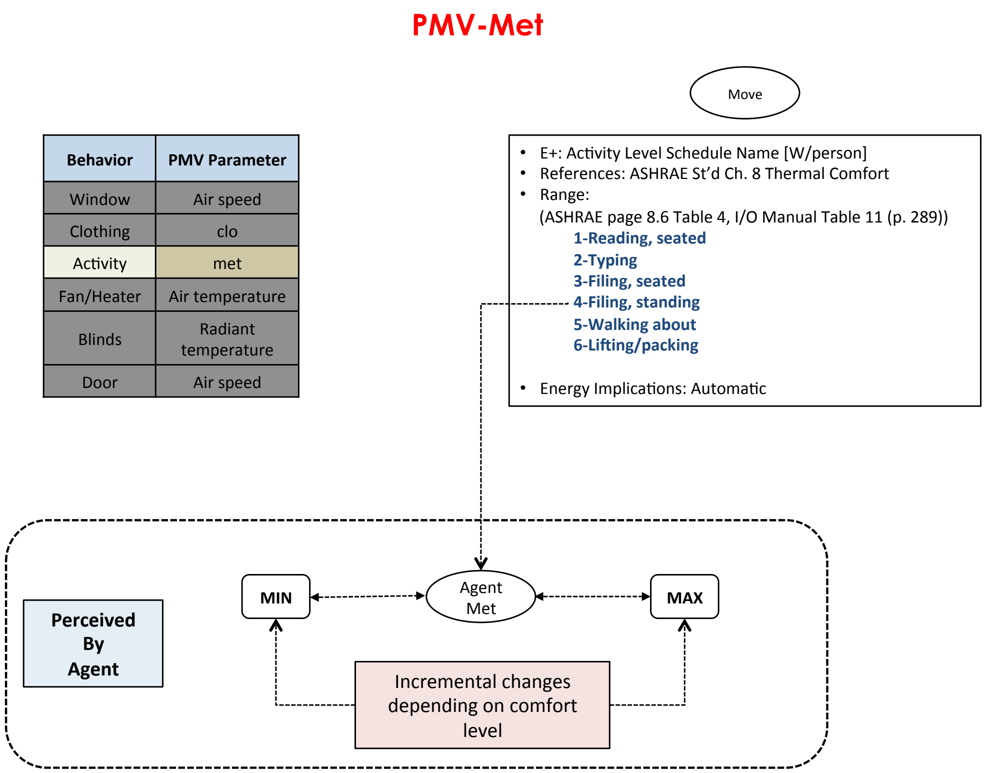
Behavior	PMV Parameter
Window	Air speed
Clothing	clo
Activity	met
Fan/Heater	Air temperature
Blinds	Radiant temperature
Door	Air speed

References: www.squ1.com, ISO7730-1993



[Met Level]

Met level is determined by agent activity levels, which are typically consistent throughout the year. Met level is also predetermined by the user, with a limited window of adjustment available for an agent in the space. Based on the input values, an agent can adjust its met level based on the increment defined in the ABM (referenced from ASHRAE Thermal Comfort Standard).

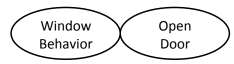


Behavior	PMV Parameter
Window	Air speed
Clothing	clo
Activity	met
Fan/Heater	Air temperature
Blinds	Radiant temperature
Door	Air speed

[Window use]

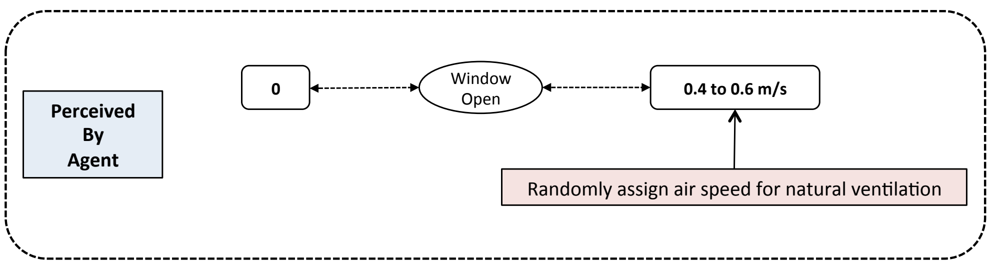
Window use behavior is defined as ‘open’ or ‘close’ with a random air speed (0.4~0.6 m/s) incurred from opening the windows.

PMV-WINDOW USE



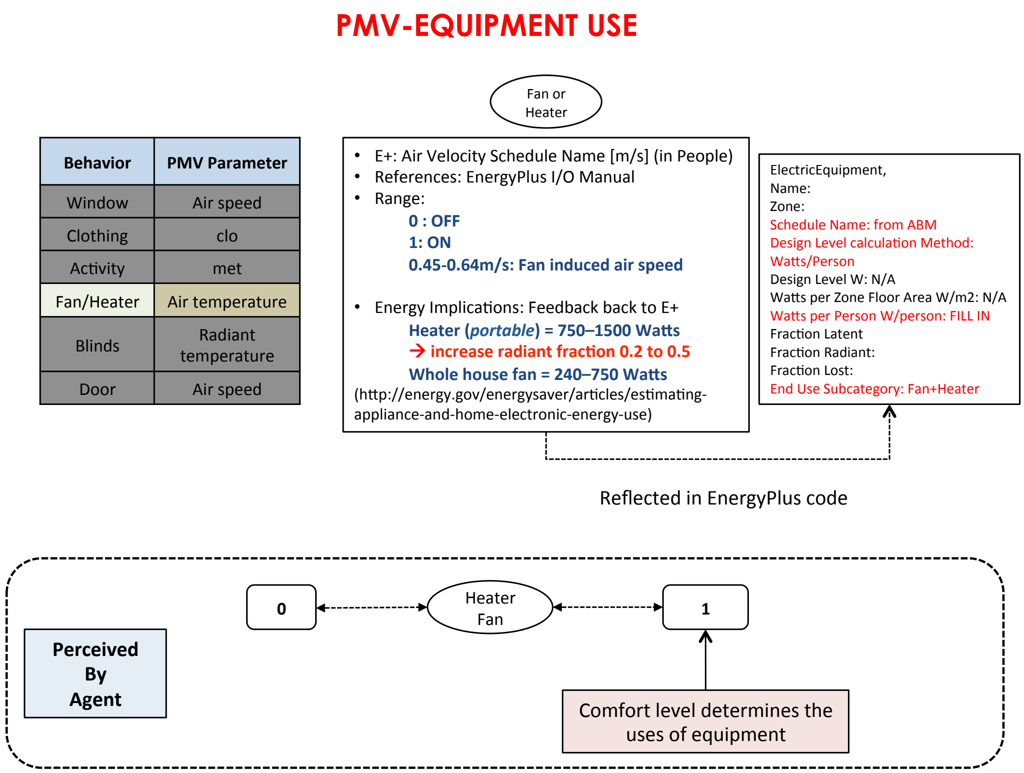
Behavior	PMV Parameter
Window	Air speed
Clothing	clo
Activity	met
Fan/Heater	Air temperature
Blinds	Radiant temperature
Door	Air speed

- E+: Activity Venting Availability Schedule
  (in AirflowNetwork:Multizone:Zone)
- References: EnergyPlus I/O Manual
- Range:
  - **0.1m/s: No air movement**
  - **~0.3m/s: Barely noticeable**
  - **~0.5m/s: Pleasant**
  - **~0.7m/s: Light breeze**
  - **~1.0m/s: Hair and paper move**
  - **~1.5m/s: Noticeably draughty**
- Energy Implications: Automatic



[Equipment use]

Equipment use concerns the added effects of personal fans and space heaters, which needs to be added to the existing EnergyPlus .idf file. The behaviors are defined as 'on' or 'off.' Similar to the window use behavior, personal fans will incur some air speed in the space, while space heaters will increase the radiant fraction.



[Blind behavior]

Blind use behavior is defined as ‘open’ or ‘close’ controlled by the zone air temperature (as the lighting level is not considered in the ABM) in the space.

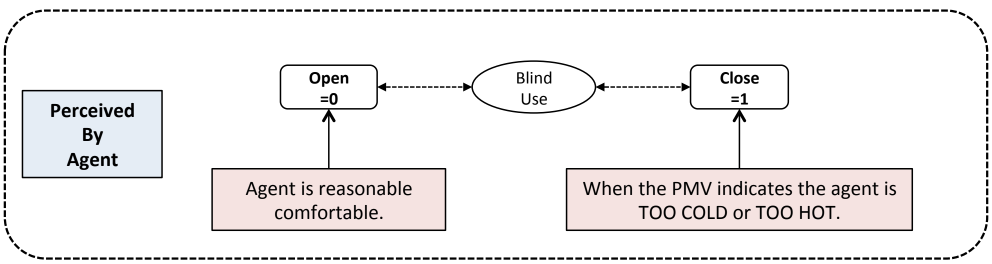
PMV-BLIND BEHAVIOR

Behavior	PMV Parameter
Window	Air speed
Clothing	clo
Activity	met
Fan/Heater	Air temperature
Blinds	Radiant temperature
Door	Air speed

References: www.squ1.com, ISO7730-1993

Blinds

- E+: WindowProperty:ShadingControl
- References: EnergyPlus I/O Manual (p. 241)
- Shading Control Type:
  - **By schedule**
  - **By diffuse solar radiation incident (W/m²)**
  - **By horizontal solar irradiance (W/m²)**
  - **By outdoor air temperature (C)**
  - **By zone air temperature (C)**
  - **By maximum glare index**
- ABM parameters: Trigger setpoint (temperature, W/m², or Watt) and control schedule.
- Energy Implications: Automatic
- Assumptions: No blind use activity when space is not occupied. *Only thermal stimulus activates the blind use behavior (future ABM will incorporate light level and glare into the decision making process)* .



APPENDIX E. Simulation coupling procedure

The steps are exercised in the dissertation to achieve simulation coupling between the Matlab ABM and EnergyPlus:

1. Download required programs
   - Download MLE+ into a folder in the computer and add paths in the Matlab environment. (https://github.com/mlab/mlep)
   - Download the latest EnergyPlus software. (http://apps1.eere.energy.gov/buildings/energyplus/)
2. Identify variables to couple (exchange)
   - ABM to EnergyPlus: All control variables including schedules related to occupancy and other behavior decisions.
   - EnergyPlus to ABM: Weather data, calculations related to thermal conditions and energy uses.
3. EnergyPlus configuration (.idf file)
   - Activate external interface to enable simulation coupling:

```
ExternalInterface,   ! – Object to activate the external interface
    PtolemyServer:   ! – Name of external interface
```

   - Define ABM variables to receive from simulation coupling:

```
! Window open/close behaviors
  ExternalInterface:Schedule,
    VentSchd,                          !- Name
    Fraction,                          !- Schedule Type Limits Name
    0;                                 !- Initial Value

! Personal fan use behaviors
  ExternalInterface:Schedule,
    DynamAir,                          !- Name
    Fraction,                          !- Schedule Type Limits Name
    0;                                 !- Initial Value
```

- Replace existing EnergyPlus syntax with the above ABM variables:
    - Define schedule names associated with agent behaviors as a consequence of the decision-making process from ABM (e.g., clothing level, activity level, window use, light use, equipment use, blind use, and so on).
    - Blind uses: Add *'WindowProperty:ShadingControl'* object and define shading control type.
    - Window uses: Add *'AirflowNetwork:MultiZone:Surface'* object that contains window properties.
    - Equipment uses: Add *'ElectricEquipment'* object and define energy use (Watt/person) for equipment entities that are related to some behavior, e.g., personal fan or space heater.

4. Matlab configuration
    - Create a function that calculates the PMV to determine the comfort level of agents. As shown on Figure 3.8, some of the parameters for PMV calculation are either behavior-specific or climate-specific. Behavior-specific parameters include clothing level and activity level, which use variables that result from the ABM decision-making process. Climate-specific parameters, such as temperature, humidity, and air speed values, are received from the EnergyPlus calculations.
    - Create a function that includes all the values that are exported and imported from EnergyPlus, and the pertinent functions that make use of the variables to run the ABM.
5. Data exchange configuration file
    - Create an XML 'variable.cfg' file in the Matlab workspace, which maps the date exchange between Matlab and EnergyPlus. The following example is an XML syntax of the 'variable.cfg' file that exchanges the following information:

- From EnergyPlus to ABM: Outdoor dry bulb temperature, zone mean air temperature, zone mean radiant temperature, and zone air relative humidity (the names and types must match the header used in the CSV file created by EnergyPlus).
- From ABM to EnergyPlus: DynamSchd (occupancy), DynamClo (clothing level schedule), DynamMet (activity level schedule), and DynamBlinds (blind use schedule).

```
<?xml version="1.0" encoding="ISO-8859-1"?>
<!DOCTYPE BCVTB-variables SYSTEM "variables.dtd">
<BCVTB-variables>

  <variable source="EnergyPlus">
   <EnergyPlus name="Environment" type="Outdoor Dry Bulb"/>
  </variable>
  <variable source="EnergyPlus">
    <EnergyPlus name="BLOCK1:ZONE1" type="Zone Mean Air Temperature"/>
  </variable>
  <variable source="EnergyPlus">
    <EnergyPlus name="BLOCK1:ZONE1" type="Zone Mean Radiant Temperature"/>
  </variable>
  <variable source="EnergyPlus">
    <EnergyPlus name="BLOCK1:ZONE1" type="Zone Air Relative Humidity"/>
  </variable>

  <variable source="Ptolemy">
    <EnergyPlus schedule="DynamSchd"/>
  </variable>
  <variable source="Ptolemy">
    <EnergyPlus schedule="DynamClo"/>
  </variable>
  <variable source="Ptolemy">
    <EnergyPlus schedule="DynamMet"/>
  </variable>
  <variable source="Ptolemy">
    <EnergyPlus schedule="DynamBlinds"/>
  </variable>
</BCVTB-variables>
```

The following Matlab .m file (customized version of MLE+) is used to perform simulation coupling for all the simulation experiments presented in the dissertation.

```
function results = coupling(schedules,winterClo,summerClo,shoulderClo,initMet,
agentBeliefs,maxdays,IDF,weatherFile,sim_timestep)

%% Create an mlepProcess instance and configure it

idfName=[char(39) IDF char(39)];
tmyName=[char(39) weatherFile char(39)];
ep = mlepProcess;
ep.arguments = {idfName, tmyName};
ep.acceptTimeout = 60000;

VERNUMBER = 2;  % Existing version upgraded to be compatible with E+ v7.1

%% Start EnergyPlus cosimulation
[status, msg] = ep.start;

if status ~= 0
    error('Could not start EnergyPlus: %s.', msg);
end

%% The main simulation loop
deltaT = 3600/sim_timestep; % (60/sim_timestep)*60
kStep = 1;  % current simulation step
MAXSTEPS = sim_timestep*24*maxdays;

TCRooLow = 22;  % Zone temperature is kept between TCRooLow & TCRooHi
TCRooHi = 26;
TOutLow = 22;  % Low level of outdoor temperature
TOutHi = 24;  % High level of outdoor temperature
ratio = (TCRooHi - TCRooLow)/(TOutHi - TOutLow);

% logdata stores set-points, outdoor temperature, and zone temperature at
% each time step. IT NEEDS TO TAKE IN THE NEW OCCUPANCY DATA.
logdata = zeros(MAXSTEPS,19);       %NEED TO UPDATE PER VARIABLES USED
pmvppd_all = zeros(MAXSTEPS,2);     %Records all PMV/PPD results
    %pmvppd_all(1)=PMV, pmvppd_all(2)=PPD
decisions=zeros(MAXSTEPS,7);
beliefs=zeros(MAXSTEPS,5);      %(clo,met,window,fanheat,blind)
costs=zeros(MAXSTEPS,5);     %(clo,met,window,fanheat,blind)

%Define initial parameters for behaviors
startPMV=0;
startMet=initMet(2);
startVent=0;        % 0=close/1=open
startHeat=0;        % 0=close/1=open
startFan=0;         % 0=close/1=open
startSpeed=0;       % air speed by an agent
startBlind=0;       % 0=open/1=close

while kStep <= MAXSTEPS
    % Read a data packet from E+
    packet = ep.read;
    if isempty(packet)
        error('Could not read outputs from E+.');
    end

    % Parse it to obtain building outputs
    [flag, eptime, outputs] = mlepDecodePacket(packet);
    if flag ~= 0, break; end


    if and(kStep>=1,kStep<=1753)
        startClo=winterClo(2);
        initClo=winterClo;
    elseif and(kStep>=1754,kStep<=3625)
        startClo=shoulderClo(2);
        initClo=shoulderClo;
```

```
elseif and(kStep>=3626,kStep<=6553)
        startClo=summerClo(2);
        initClo=summerClo;
    elseif and(kStep>=6554,kStep<=8015)
        startClo=shoulderClo(2);
        initClo=shoulderClo;
    else
        startClo=winterClo(2);
        initClo=winterClo;
    end


    if schedules(kStep)>0
        % The Heating set-point: day -> 22/20, night -> 12
        % The cooling set-point is bounded by TCRooLow and TCRooHi

        %Initial agent beliefs on behaviors(clo,met,window,fan/heat) for [control,
        %perception,normative]
        startCost=costFunction(agentBeliefs);
        startThink=agentThink(startPMV,startCost);

        %Initial behaviors
        startClo=behavClo(startPMV,startClo,initClo);
        startMet=behavMet(startPMV,startMet,initMet);
        startWin=behavWindow(startPMV,startVent,startSpeed);
        startFanHeat=behavHeatFan(startPMV,startSpeed,startFan,startHeat);
        startBlind=behavBlind(startPMV,startBlind,0);

        newDecisions=agentDecide(startThink,startClo,startMet,startWin,
        startFanHeat,startBlind);
        newPMV=FangerPMV(newDecisions.clo,newDecisions.met,0,outputs(2),outputs(3),
        newDecisions.speed,outputs(4),0);
        nextBelief=simulation(startThink,agentBeliefs,startPMV,newPMV(1));


        SP = [20, max(TCRooLow, min(TCRooHi, TCRooLow + (outputs(1) –
              TOutLow)*ratio)), ...

        schedules(kStep),newDecisions.clo,newDecisions.met*104.58,newDecisions.vent
        ,newDecisions.speed,newDecisions.fan,newDecisions.heat,newDecisions.blind];

        startPMV=newPMV(1);

        decisions(kStep,1)=newDecisions.clo;
        decisions(kStep,2)=newDecisions.met;
        decisions(kStep,3)=newDecisions.vent;
        decisions(kStep,4)=newDecisions.fan;
        decisions(kStep,5)=newDecisions.heat;
        decisions(kStep,6)=newDecisions.speed;
        decisions(kStep,7)=newDecisions.blind;

        beliefs(kStep,1)=nextBelief.perception.clo;
        beliefs(kStep,2)=nextBelief.perception.met;
        beliefs(kStep,3)=nextBelief.perception.window;
        beliefs(kStep,4)=nextBelief.perception.fanheat;
        beliefs(kStep,5)=nextBelief.perception.blind;

        %'clo','met','window','fanheat','blind'
        costs(kStep,1)=startCost(1).value;
        costs(kStep,2)=startCost(2).value;
        costs(kStep,3)=startCost(3).value;
        costs(kStep,4)=startCost(4).value;
        costs(kStep,5)=startCost(5).value;

        pmvppd_all(kStep,1)=newPMV(1);
        pmvppd_all(kStep,2)=newPMV(2);
```

```
        if schedules(kStep+1)==0
            startClo=initClo(2);
            startMet=initMet(2);
            startVent=0;                    % 0=close/1=open
            startHeat=0;                    % 0=close/1=open
            startFan=0;                     % 0=close/1=open
            startSpeed=0;
            startBlind=0;

            % Assumes beliefs renew each day.
            nextBelief.perception.clo=agentBeliefs.perception.clo;
            nextBelief.perception.met=agentBeliefs.perception.met;
            nextBelief.perception.window=agentBeliefs.perception.window;
            nextBelief.perception.fanheat=agentBeliefs.perception.fanheat;
            nextBelief.perception.blind=agentBeliefs.perception.blind;
            agentBeliefs=nextBelief;

        else
            startClo=newDecisions.clo;
            startMet=newDecisions.met;
            startVent=newDecisions.vent;         % 0=close/1=open
            startHeat=newDecisions.heat;         % 0=close/1=open
            startFan=newDecisions.fan;          % 0=close/1=open
            startSpeed=newDecisions.speed;
            startBlind=newDecisions.blind;
            agentBeliefs=nextBelief;
        end
    else
        % The Heating set-point: day -> 22, night -> 12
        % The Cooling set-point: night -> 30
        SP = [20, max(TCRooLow, min(TCRooHi, TCRooLow + (outputs(1) -
             TOutLow)*ratio)),schedules(kStep),0,0,0,0,0,0,0];

        decisions(kStep,1)=0;
        decisions(kStep,2)=0;
        decisions(kStep,3)=0;
        decisions(kStep,4)=0;
        decisions(kStep,5)=0;
        decisions(kStep,6)=0;
        decisions(kStep,7)=0;

        pvmppd_all(kStep,1)=0;
        pmvppd_all(kStep,2)=0;
    end
    % END

    % Write to inputs of E+ (configured in variables.cfg)
    ep.write(mlepEncodeRealData(VERNUMBER, 0, (kStep-1)*deltaT, SP));

    % Save to logdata
    logdata(kStep, :) = [SP outputs];

    kStep = kStep + 1;
end

% Stop EnergyPlus
ep.stop;

disp(['Stopped with flag ' num2str(flag)]);

% Remove unused entries in logdata
kStep = kStep - 1;
if kStep < MAXSTEPS
    logdata((kStep+1):end,:) = [];
end

results=struct('setH',logdata(:,1),'setC',logdata(:,2),'schd',logdata(:,3));

end
```

APPENDIX F. ABM class diagram

The overall ABM process from a simulation program's point of view is illustrated in Figure F.1. It indicates ABM components that are programmed in Matlab (by the author), along with how they are connected to the external simulator for simulation coupling. As mentioned in Section 3.4, simulation coupling adopts the framework of BCVTB and MLE+.

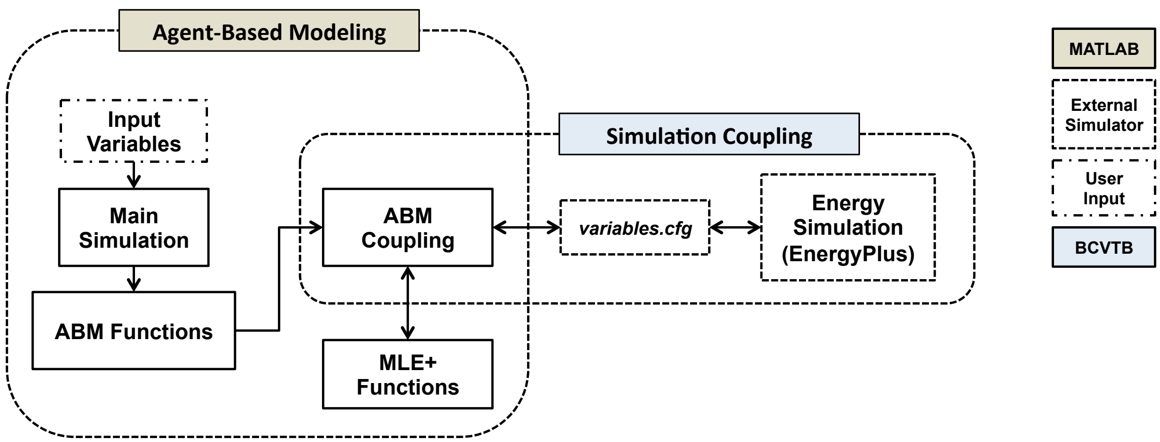


Figure F.1 ABM process from a point of view of the simulation program

The following is a class diagram [Silverman, 2010] of the dissertation's ABM process delineated in Matlab codes. Each box represents a function as an .m file, while the dotted boxes represent external simulators that constitute the simulation coupling process. The actual codes for simulation coupling are presented in Appendix E.

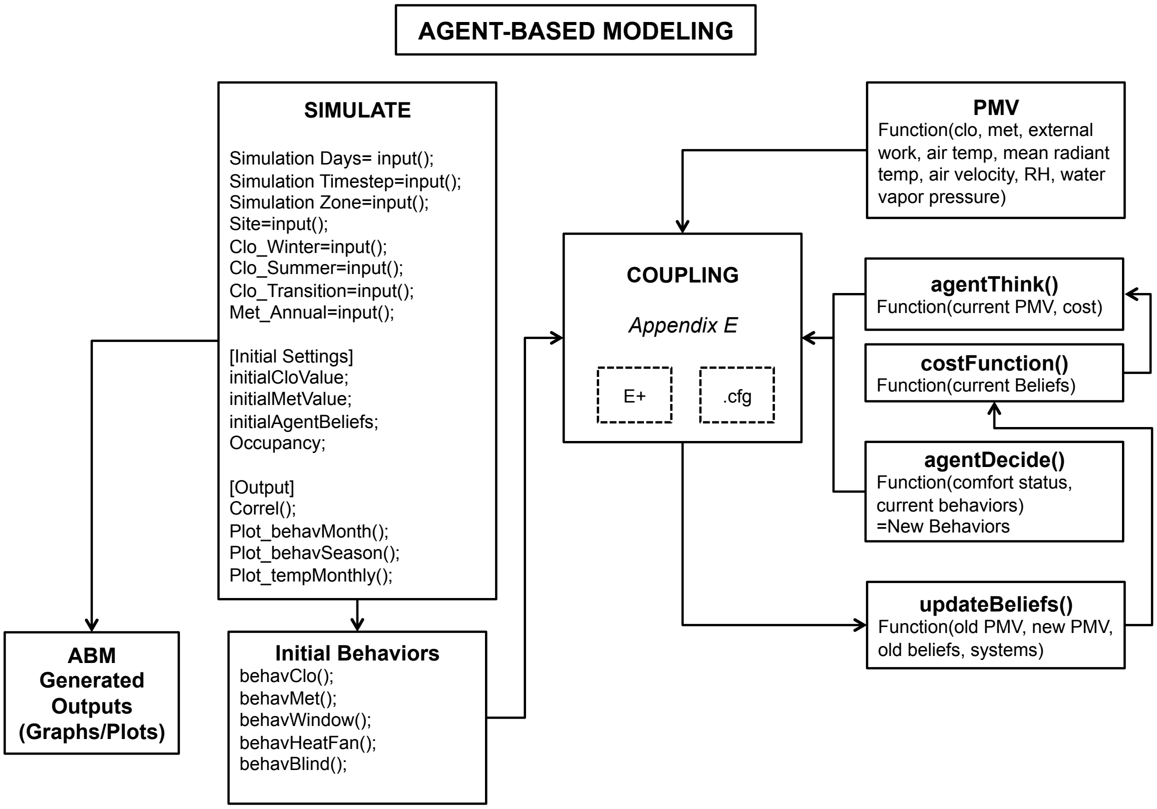


Figure F.2 Class diagram of ABM process

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